Development and Validation of a Neighbourhood Disaster Resilience Index : A Case Study from Australia

Author

Irajifar, Leila

Published

2016

Thesis Type

Thesis (PhD Doctorate)

School

Griffith School of Environment

DOI

10.25904/1912/330

Development and Validation of a Neighbourhood Disaster Resilience Index

A Case Study from Australia

A Dissertation

by

Leila Irajifar (B.A., M.Sc.)

Submitted to the Griffith School of Environment

Science, Environment, Engineering and Technology

Griffith University

In fulfilment of requirements of the degree of

Doctor of Philosophy

February 2016

ABSTRACT

Development and Validation of a Neighbourhood Disaster Resilience Index:
A Case Study from Australia

Since the adoption of the Hyogo Framework for Action in 2005 'Building the resilience of nations and communities to disasters', the concept of disaster resilience has attracted substantial attention among researchers and practitioners. Although recent disaster literature refers to resilience as a managerial principle of an effective disaster risk management, there are still critical challenges in making resilience operational and adopting it in planning and decision making. Currently available resilience measurement frameworks are mostly focused on large spatial scales such as sub-national/regional levels and do not meet the local needs of designers and planners, while communities are the focus of mitigation and recovery planning, with unique local socio-economic and physical characteristics, and inherent adaptation potential. More specifically, urban form characteristics are assumed by several studies to contribute to the disaster resilience of communities. However, such an assumption has not been examined empirically and urban form factors are mostly under-represented in the resilience models. In addition, sensitivity, reliability and validity of the resilience models have not been addressed comprehensively, and when it comes to the Australian context, resilience models have not been validated at all.

The purpose of this dissertation is to address the above gaps through (1) development of a Neighbourhood Disaster Resilience Index (NDRI) with emphasise on resilience attributes within community elements; and (2) validation of the proposed index (NDRI) by assessing the extent to which it contributes to real-world recovery outcomes and pathways following the 2011 floods in the Brisbane and Ipswich neighbourhoods, using readily available longitudinal reconstruction data.

The dissertation builds upon resilience attributes and develops a conceptual framework of disaster resilience indicators at neighbourhood level. The indicators are analysed to reduce the dimensionality of the data, to gain a parsimonious set of indicators, and to calculate alternative composite scores using different weighting and aggregation methods. The sensitivity of each composite indicator is then evaluated, and the equal weighting and linear aggregation scheme is selected as it shows less sensitivity and has a more robust, balanced structure.

The contribution of urban form factors (including density, land use mix and building type diversity) to the recovery progress is examined to improve understanding of the relationship between NDRI's physical component and the recovery outcomes. The results show that compact neighbourhoods in the study area recovered more quickly than the spread out ones. A series of regression and correlational analysis are utilised to assess the construct and incremental validity of the proposed index (NDRI). The results show convincing empirical confirmation that the index is valid and reliable. A cross-comparative study of flood affected neighbourhoods in the study area also shows strong links between identified resilience indicators and the recovery outcomes. The results show the potential for successful recovery stemming from different interrelated conditions with respect to a range of socio-economic resources and urban form conditions available. Such conclusion provides an improved understanding of the resilience and recovery at local level. The results can assist planners and managers to prioritize and concentrate their interventions on the conditions and areas that best support neighbourhoods' capacity and resources to respond and recover from a shock.

ACKNOWLEDGEMENTS

The completion of this thesis was contingent on the support and encouragement of many people. I must first acknowledge Griffith University for granting me a full scholarship which gave me the opportunity to focus on my research and improve my academic skills.

I would like to sincerely thank my supervisors Dr Tooran Alizadeh and Professor Neil Sipe who have guided my research over the past years; their advice has been invaluable from the beginning of my research. My appreciation also goes to Dan Lewis and Cassidy Johnson for giving me the chance to be part of the City Resilience Profiling Program which provided me with valuable insights into the index development process, familiarizing me with tangible, practical aspects of urban resilience.

Last but certainly not least, I would like to thank my family. I appreciate the great support and encouragement my beloved husband, Sina has given me. I would like to thank my parents' for their boundless support and love, dear Maman and dear Baba. I am also grateful to my three dear siblings Nazanin, Mehrdad and Mahyar for cheering me up during the hard times.

Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Table of Contents

List of Figures

List of Tables

Papers Published from this Thesis

The papers that have been presented in conferences and/or have been published based on the chapters of this thesis are listed below:

- **Irajifar, L.**, Sipe, N., Alizadeh. T., 2016 [accepted on 19.10.2015]. The impact of urban form on disaster resiliency: A case study of Brisbane and Ipswich, Australia. International journal of disaster resiliency in built environment. In press.
(This paper is extracted from Chapter 8 of this dissertation)

- **Irajifar, L.**, Alizadeh. T., Sipe, N., 2015. Neighbourhood Disaster Resilience Index: A validation in the context of Brisbane and Ipswich 2011 flood. Proceedings of the State of Australian Cities National Conference. 9-11 December 2015. Gold Coast, Australia.
(This paper is extracted from Chapters 5, 6, 7 of this dissertation)

- **Irajifar, L.**, Alizadeh. T., Sipe, N., 2015. Resilience Assessment: Recovery of Brisbane Neighbourhood after 2011 floods. Proceedings of the 7th International i-Rec Conference. 6-8 July 2015. University College London, London, UK.
(This paper is extracted from Chapter 9 of this dissertation)

- **Irajifar, L.** Alizadeh, T., Sipe, N., 2013. Disaster resiliency measurement frameworks: state of the art. Proceedings of CIB World Building Congress on construction and society. 5-9 May 2013. Brisbane, Australia.
(This paper is extracted from Chapter 2 of this dissertation)

Chapter 1
Introduction

1. Introduction

1.1. Preface

The frequency and intensity of natural hazards are increasing globally (Figure1.1). The Intergovernmental Panel on Climate Change (IPCC) argues that climate change will continue to intensify the meteorological events in the future (Solomon, 2007). At the same time, the growing intensity of settlements and concentration of assets in hazardous areas further contribute to vulnerability in the future (Munich Re Group, 2009). Thus, improving the disaster resilience of communities is critical.

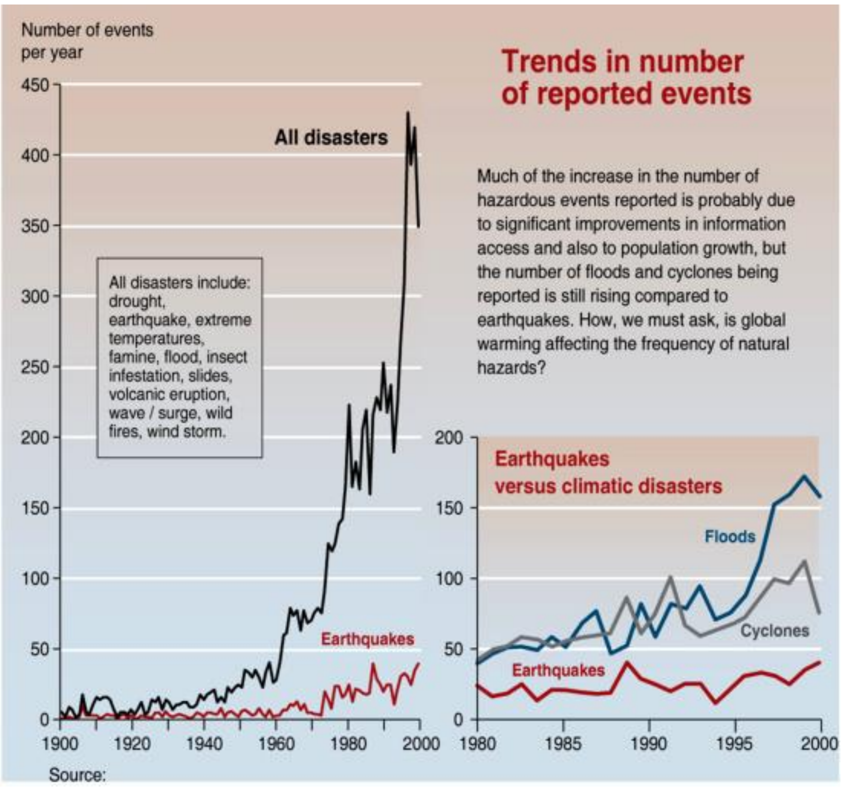


Figure 1.1 Trends in number of reported events
(United Nations Environment Programme (UNEP))

It is now understood that complete protection from risk is neither technically possible nor economically feasible (Godschalk, 2003). As a result, concepts such as resilience have become more dominant in the field of risk management and planning. A resilient community is the one that does not experience serious degradation in critical services when a hazard occurs, and in the event of degradation or failure, recovers to a similar or better level of service in a reasonable amount of time (Gallopín, 2006). As a concept, disaster resilience is still in its infancy stage in disaster management and planning (Tierney, 2009; Wardekker et al., 2010). In many cases, there is limited theoretical understanding of how it should be operationalized (Chelleri, 2012; Wilkinson, 2012b; Windle et al., 2011).

This research seeks to improve the current state of knowledge on urban disaster resilience within the broader field of disaster management, with a focus on the built environment. While researchers including Tierny (2009), Norries (2008) and Walker (2012) have sought to explain the causal structure of disaster resilience, the ability to measure resilience is progressively being understood as a key step towards disaster risk reduction. To enhance disaster resilience, it is necessary to understand its determinants, how it can be measured, and how it can be maintained and improved (Cutter et al., 2008; Klein et al., 2003).

1.2. Problem Statement

Since the adoption of the Hyogo Framework for Action 2005-2015 (UNISDR, 2005) 'Building the resilience of nations and communities to disasters', the concept of disaster resilience has gained wider interest and has become more popular among academic researchers and practitioners. Although the recent disaster literature (Stumpp, 2013; Walker & Salt, 2012; Wilkinson, 2012b) refers to resilience as a managerial principle behind effective hazard risk management, there are critical challenges in making it operational in terms of its determinants and evaluation methods. In recent years, several models have been developed for operationalizing and measuring the disaster resilience of communities at different contexts and scales. However, a thorough review of literature on the current approaches (Chapter 2) identifies gaps in operationalising and adopting these models for planning and decision-making:

- Operationalization and measurement of disaster resilience at neighbourhood level which comprehensively considers the physical, social, economic and environmental conditions, has not been addressed,. The current resilience models are mostly focused on large scales which do not meet local needs for urban designers and planners, since each neighbourhood has its own unique socio-economic and physical characteristics.

  In recent years, many disaster researchers have emphasized the importance of operationalising resilience (Carpenter et al., 2001; Cutter et al., 2008; Deppisch & Schaerffer, 2011; Sherrieb et al., 2010; Windle et al., 2011). Cutter et al. (2003), Renschler et al. (2010), Shaw et al. (2009) and Chang et al. (2004) have developed metrics for measuring resilience. Despite this emphasise on measuring resilience, a comprehensive model of disaster resilience at the neighbourhood level is still lacking (Mayunga, 2009; Stumpp, 2013; Wardekker et al., 2010; Winderl, 2015). The concept of disaster resilience in existing models has primarily been examined at large spatial scales, the sub-national/ regional level. However, communities at the local scale are the focus of hazard mitigation, disaster preparedness, disaster response, and disaster recovery planning. Thus, assessing disaster resilience at a large scale may not be useful or meet local needs, especially for urban planners and designers. Bridging this gap in resilience modelling at a smaller scale would provide a better picture of how communities/neighbourhoods, are performing in regard to disaster resilience. The fundamental motivation for down-scaling resilience assessment comes from understanding that each neighbourhood has unique physical characteristics, as well as inherent adaptation potential.

- In addition, the reliability and validity of existing resilience models has not been addressed comprehensively. Thus it is important to examine the extent to which the resilience model proposed in this thesis and its components contribute to real-world recovery outcomes and pathways. Several studies (Allan et al., 2013; Hurlimann & March, 2012) have emphasized the link between urban form and disaster resilience. This hypotheses needs to be examined empirically to check whether they are appropriate for consideration in resilience modelling. Moreover, to understand differences in recovery processes and to understand the link between the pre/post-disaster conditions of communities and recovery outcomes, a broad cross-case comparative study is needed.

Evaluating reliability and validity of disaster resilience measures is challenging due to the lack of data in post disaster damage assessments and recovery times. For this reason, the reliability and validation of resilience models face many constraints, and their contribution to recovery outcomes has not been comprehensively addressed by previous studies (Ahern, 2011; Boyd et al., 2008; Leichenko, 2011; Seto et al., 2010).

In addition, there is a need to investigate the relationship between pre/post disaster conditions and recovery outcomes (Smith & Wenger, 2007) to address the critiques on the difficulty of meaningful interpretation of the resilience models (Hezri & Dovers, 2006) and the lack of causal linkages between the indicator values and the desired outcomes (Briassoulis, 2001). This can be addressed by cross-case comparative studies which are very few in the fields of community vulnerability, resilience and recovery, while there have been many individual case studies in recovery progress (Chang et al., 2010; Olshansky et al., 2008).

1.3. Research Questions

To address the research gaps mentioned above, this research seeks to answer two overarching questions:

- ***How can an urban disaster resilience model be developed at the neighbourhood level?***
- ***How can the neighbourhood disaster resilience model be validated by assessing its contributions to the recovery outcomes?***

To address the first question, a number of sub-questions have been developed:

- What is the nature of the resilience construct's conceptual domains and properties?
- What are the key indicators of disaster resilience at the neighbourhood level?
- What set of variables provides a parsimonious set of disaster resilience indicators at the neighbourhood level? and
- How can these indicators be merged into a composite resilience index?

A neighbourhood level disaster resilience measurement model is proposed and all the required steps for model specifications, indicators selection, dimension reduction and aggregation of indicators to a composite index will be investigated.

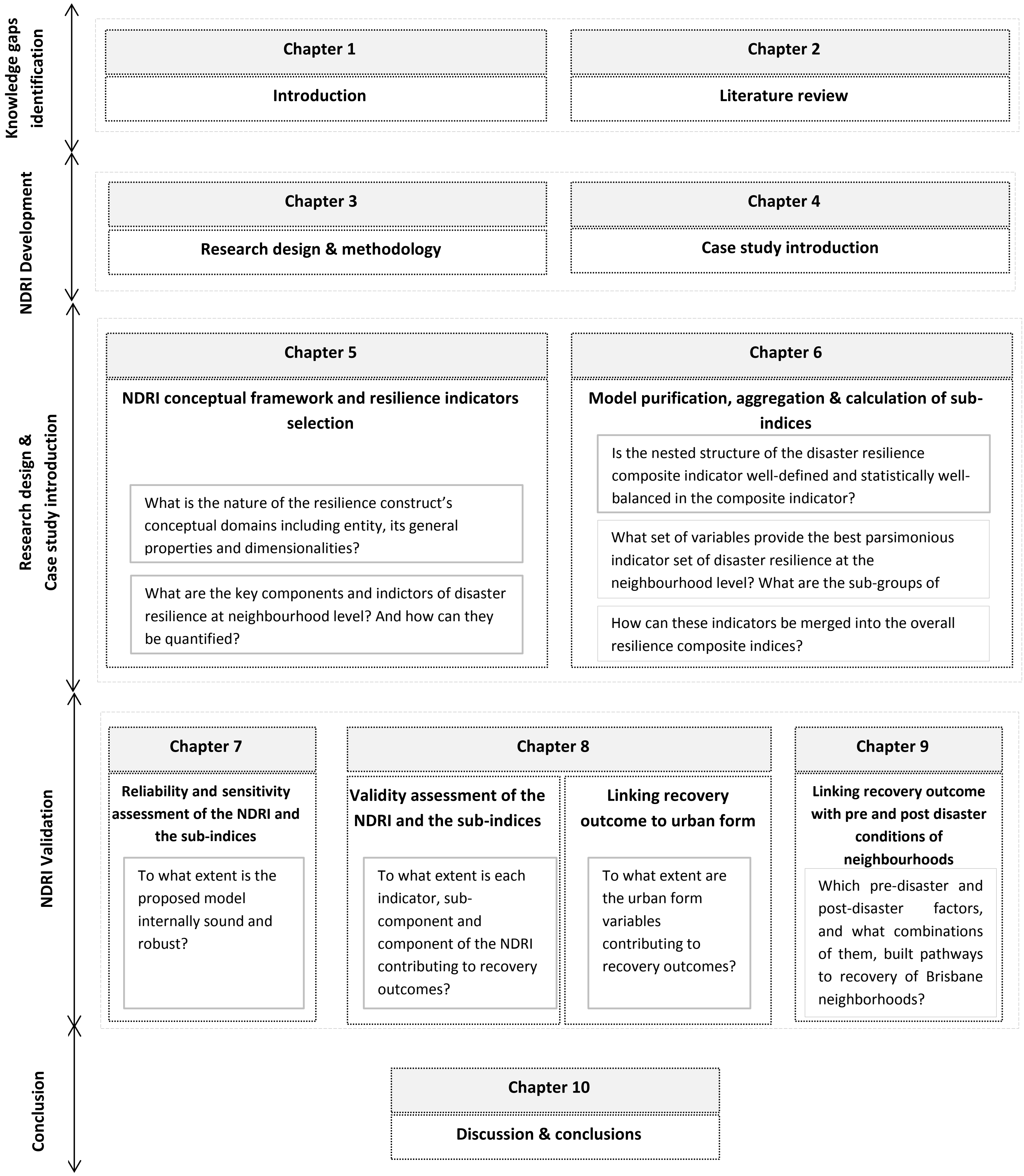
To answer the second research question, the contribution of the Neighbourhood Disaster Resilience Index (NDRI) and its components (including the urban form factors) to recovery outcomes and pathways in case study neighbourhoods is evaluated.

- To what extent is the proposed model internally sound and robust?
- To what extent is each indicator, sub-component and component of the NDRI contributing to recovery outcomes?
- To what extent are the urban form variables contributing to recovery outcomes?
- Which pre-disaster conditions and post-disaster factors, and what combinations of these, build pathways to recovery?

1.4. Thesis Structure

This thesis addresses the existing gaps in disaster resilience literature and the identified research questions using a range of different methods from content analysis to various statistical analyses. An overview of the thesis structure is provided in Figure 1.3.

The thesis contains ten chapters and is organized around five parts. The first part (Chapters 1 and 2) identifies the gaps in the literature. The first chapter, the introduction, provides some background on the topic, the problem statement and the research questions. Chapter Two provides a review of the literature on urban disaster resilience and an assessment of the state of the art in modelling disaster resilience. Existing disaster resilience models were analyzed using seven criteria to identify their strengths and weaknesses.


Knowledge gaps identification
Chapter 1
Introduction
Chapter 2
Literature review
NDRI Development
Chapter 3
Research design & methodology
Chapter 4
Case study introduction
Research design & Case study introduction
Chapter 5
NDRI conceptual framework and resilience indicators selection
What is the nature of the resilience construct's conceptual domains including entity, its general properties and dimensionalities?
What are the key components and indictors of disaster resilience at neighbourhood level? And how can they be quantified?
Chapter 6
Model purification, aggregation & calculation of sub-indices
Is the nested structure of the disaster resilience composite indicator well-defined and statistically well-balanced in the composite indicator?
What set of variables provide the best parsimonious indicator set of disaster resilience at the neighbourhood level? What are the sub-groups of
How can these indicators be merged into the overall resilience composite indices?
NDRI Validation
Chapter 7
Reliability and sensitivity assessment of the NDRI and the sub-indices
To what extent is the proposed model internally sound and robust?
Chapter 8
Validity assessment of the NDRI and the sub-indices
To what extent is each indicator, sub-component and component of the NDRI contributing to recovery outcomes?
Linking recovery outcome to urban form
To what extent are the urban form variables contributing to recovery outcomes?
Chapter 9
Linking recovery outcome with pre and post disaster conditions of neighbourhoods
Which pre-disaster and post-disaster factors, and what combinations of them, built pathways to recovery of Brisbane neighborhoods?
Conclusion
Chapter 10
Discussion & conclusions

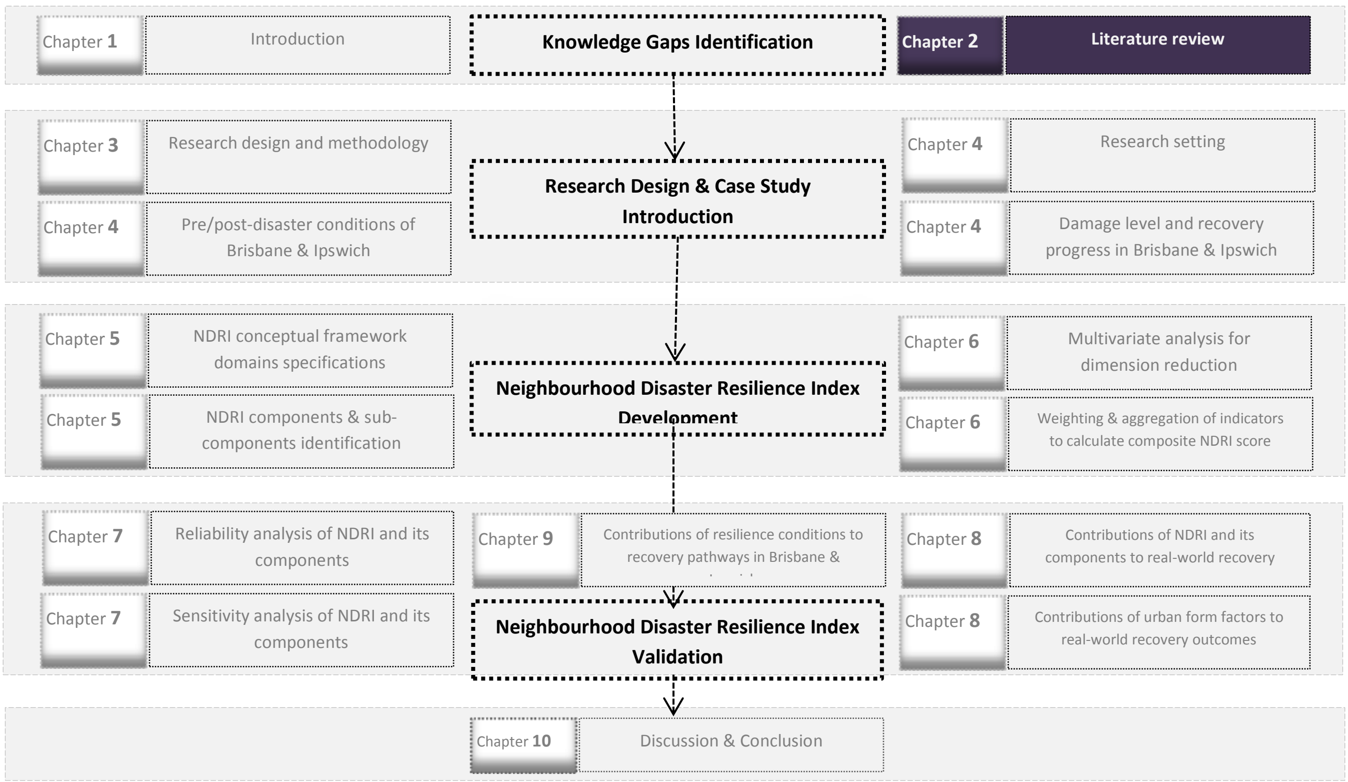
The second part of the thesis, Chapters 3 and 4, describes the research methodology and introduces the case study. Chapter 3 describes the research strategy and the justification for the scientific paradigm of this research. The case study is introduced in Chapter 4 and provides the pre/post disaster conditions of the included neighbourhoods, as well as documenting their recovery progress.

Chapter 5 and Chapter 6 make up the third part of the thesis which focuses on the Neighbourhood Disaster Resilience Index (NDRI) development procedure. Chapter 5 elaborates on conceptualization of resilience in this research, the dimensionality and other specifications of the intended model to generate a framework for indicator selection. A list of indicators is proposed based on the theoretical framework. These indicators are refined in Chapter 6 using multivariate analysis for dimension reduction. Finally, Chapter 6 provides the procedure for calculating the composite NDRI.

Part four (Chapters 7, 8 and 9) presents attempts to validate the NDRI. In Chapter 7, the reliability of the proposed index is evaluated using inter-item correlation analysis and stratified Cronbach alpha. Moreover, in Chapter 7, sensitivity analysis is conducted to assess the robustness of the index and to evaluate the effects of individual sources of uncertainty on the final score's variance. The uncertain inputs in this analysis include: 1) inclusion and exclusion of the urban form indicators; 2) using alternative weighting systems including PCA and EW weighting systems; and 3) using different aggregation schemes including linear and geometric systems. In Chapter 8, the damage and recovery outcomes identified in Chapter 4 are utilised as real world resilience outcomes to validate the proposed model NDRI and to test the contribution of urban form factors to disaster recovery outcomes. Furthermore, in Chapter 9, these results are utilised to conduct the cross-case comparative analysis of recovery outcomes (using fsQCA software) to find the pre/post disaster resilience conditions and their combinations that lead to these recovery outcomes.

The last part of the thesis (Chapter 10) provides the discussion and conclusion. It summarizes the theoretical and practical contributions of the thesis and lays the groundwork for future studies on operationalising disaster resilience in an urban context. Additional technical details related to the analysis are provided in the appendices.

Chapter2
Critical Literature Review



2. Critical Literature Review

2.1. Overview

The concept of disaster resilience has gained wide interest among academic researchers and practitioners. Despite the recurrent referral to resilience in the literature and practical planning documents, operationalizing this concept in the urban and regional planning context raises critical challenges in terms of its determinants and assessment and has not been addressed thoroughly.

There exist a number of disaster resiliency frameworks and models with varying degrees of comprehensiveness, accuracy and validity which offer communities a set of indicators to measure and manage their resilience, preserve their critical structures and functions in the face of disturbances and recover quickly to the desired pre-disaster conditions. Accordingly, this chapter examines the dominant literature on disaster resilience measurement approaches within the international urban resilience literature. The first section details the conceptual domains of disaster resilience including its definitions, attributes and components. Following this section, current approaches in disaster resilience modelling are explored by studying and categorising a series of already established resilience models.

Later, seven criteria are considered for critical analysis of resiliency models to align them with the urban studies discipline and to identify the downsides and gaps in current approaches. This critical analysis is based on seven criteria: comprehensiveness, structure of components and indicator building methods, scale and unit of analysis, dynamics, data requirements, validation and operationality, and actual and potential applications. This chapter ends by speculating about the gaps in the current resilience measurement approaches and the most promising opportunities to further improve the resiliency models in urban contexts.

2.2. Conceptual Consolidation of Disaster Resilience

As a concept, resilience is applied in many disciplines including hazards, ecology, psychology, sociology, geography, psychiatry, public health and urban planning (Bahadur & Thornton, 2015; Folke, 2006; Gilbert, 2010). It has been defined in a variety of ways and has many different connotations, depending on the discipline. The primary focus of this study is on the concept of "disaster resilience" as applied to the field of hazards and risk mitigation in urban planning. Below is a summary of the different definitions of the concept of resilience related to the scope of this study.

Table 2.1 Selected definitions of resilience in the field of disaster and hazards

Authors	Definition
(Timmerman, 1981)	Resilience is the measure of a system's or part of a system's capacity to absorb and recover from a hazardous event.
(Wildavsky, 1988)	Resilience is the capacity to cope with unanticipated dangers after they have become manifested. It is also learning to bounce back.
(Buckle et al., 2000)	Resilience is the capacity that people or groups may possess to withstand or recover from emergencies and which can stand as a counterbalance to vulnerability.
(Mileti, 1999)	Local resilience with regard to disasters means that a local community is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life without a large amount of assistance from outside the community.
(Comfort et al., 1999)	The capacity to adapt existing resources and skills to new systems and operating conditions.
(Paton & Johnston, 2001)	Resilience describes an active process of self - organising, learned resourcefulness and growth - the ability to function psychologically at a level far greater than expected given the individual's capabilities and previous experiences.
(Waller, 2001)	Resilience is the capacity to survive, adapt and recover from a natural disaster. Resilience relies on understanding the nature of possible natural disasters and taking steps to reduce risk before an event, as well as providing for quick recovery when a natural disaster occurs. These activities necessitate institutionalised planning and response networks to minimize diminished productivity, devastating losses and decreased quality of life in the event of a disaster.
(Carpenter et al., 2001)	Resilience indicates these three properties of the system: (i) The amount of change that the system can undergo and still maintain the same structure, function and controls. (ii) The degree to which the system is able to self-organise. (iii) The degree to which the system can build the capacity to learn and adapt.
(Pelling, 2003)	Resilience is the ability of an actor to cope with or adapt to hazard stress.
(Godschalk, 2003)	A resilient city is a sustainable network of physical systems and human communities.
(UNISDR, 2005)	Resilience is the capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of function and structure. This is determined by the degree to which the social system is capable of organising itself to increase this capacity for learning from past disasters for better future protection and improve risk reduction measures.
(Maguire & Hagan, 2007)	Social resilience is the capacity of social entity to bounce back or respond positively to adversity. Social resilience has three major properties, resistance, recovery and creativity.
(Haimes et al., 2008)	The ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and composite costs and risks.

As Table 2.1 shows, Timmerman (1981) was the first to introduce the concept of resilience in the field of hazard and risk mitigation using climate change as a case in his paper entitled "Vulnerability, Resilience, and the Collapse of Societies". Borrowing the concept of resilience from the field of ecology, Timmerman (1981) linked resilience to hazard vulnerability and defined resilience as the measure of a system's or sub-system's capacity to absorb and recover from a hazardous event (Clark et al., 1998; Klein et al., 2003). Following the work of Timmerman, many definitions of the concept of disaster resilience have emerged in this field during the last three decades. Similarly to the field of ecology, there is currently no universal definition of disaster resilience in the field of hazards and risk mitigation. This is perhaps expected because hazards and disaster research has been conducted by different researchers from different disciplines with different backgrounds. In general, it can be said that resilience studies include four distinct themes, including resilience as a biophysical attribute, a social attribute, a social-environmental system (SES) attribute and an attribute of specific areas (Zhou et al., 2010).

Outcome-oriented definitions describe resilience in terms of the final results. An outcome-oriented definition would delineate resilience in terms of degree of recovery, time to recovery, or extent of damage avoided. For example, Heinz at al. (2006, p. 145) describes a “disaster resilient community” as “a community built to reduce losses to humans, the environment, and property as well as the social and economic disruptions caused by natural disasters”. However, process-oriented definitions have been preferred by disaster researchers from social sciences. For example, Norris et al. (2008, p. 133) delineate resilience as “a process linking a set of adaptive capacities to a positive trajectory of functioning and adaptation after a disturbance”.

The wide use of resilience shows its significance in disaster literature but it has been used in some cases that stretched the concept beyond its original meaning, to the point that the concept itself runs the risk of becoming pointless and a source of theoretical misunderstanding (Davoudi et al., 2012; Hambleton, 2015). Moreover, there are a few linked terms to resilience such as resistance, vulnerability and sustainability in disaster studies, which have to be defined carefully to avoid using them in incompatible ways.

Table 2.2. Comparison of resilience with similar linked terms

Term	Comparison with Resilience
Vulnerability	"In some cases disaster resilience is understood as the opposite of vulnerability. They are not totally mutually exclusive, nor totally mutually inclusive. Vulnerability is the pre-event, inherent characteristics or qualities of social systems that create the potential for harm (Cutter et al., 2008).Vulnerability is a function of the exposure (who or what is at risk) and sensitivity of system (the degree to which people and places can be harmed) (Adger, 2000; Miller et al., 2010). In contrast, resilience is the ability of a social system to respond and recover from disasters and comprises those inherent conditions that allow the system to absorb impacts and cope with an event, as well as post-event, adaptive processes that facilitate the ability of the social system to re-organize, change, and learn in response to a threat."(Tierney, 2009)
Resistance	Norris et al. (2008) makes a distinction between resilience and resistance. In their terminology resilient communities and people bounce back from disasters, while resistant communities and people do not suffer harm from hazards in the first place. In fact, it can be considered as an attribute of resilience.
Adaptive capacity	"Some authors equate adaptive capacity with resilience and social resilience. Gunderson (2000) defines adaptive capacity as system robustness to changes in resilience, Carpenter et al. (2001) use adaptive capacity as a component of resilience that reflects the learning aspect of system behaviour in response to disturbance, and Walker et al. (2004) define adaptability as the collective capacity of the human actors in an SES to manage resilience, including making desirable basins of attraction wider and/or deeper, and shrinking undesirable basins; creating new desirable basins, or eliminating undesirable ones; and changing the current state of the system so as to move either deeper into a desirable basin, or closer to the edge of an undesirable one." (Smith & Wenger, 2007).
Sustainability	Some authors consider resilience as a property of sustainability. Extending the idea of ecologists who argue that resilience promotes sustainable ecosystems. Sustainability, within the context of natural disasters is defined as the ability to ''tolerate—and overcome—damage, diminished productivity, and reduced quality of life from an extreme event without significant outside assistance'' (Mileti 1999) Unsustainable practice's stresses on the environment may cause in more severe environmental hazards. Large-scale deforestation for example, was a factor in increasing the flooding hazard in the 1998 floods in China (Wisner et al., 2004)
Sensitivity	"A sensitive system may or may not be resilient. An insensitive system (i.e., an ''armoured system'') may exhibit low vulnerability and low resilience (it is the exposure to perturbation that builds resilience in natural systems). Sensitivity may open a system to threats, but an insensitive system may be unable to adapt and seize opportunity (Gallopín, 2006). Sensitivity is an inherent property of an SES; distinguished from its capacity of response (the actual transformation may be smaller, depending on the capacity of response of the system). It is an attribute of the system, existing prior to the perturbation, and separate from exposure." (Gallopín, 2006)

2.2.1. Resilience Attributes in an Urban Context

In a general social-environmental context, four attributes of resilience were first described by Hollings (1973) and were expanded on by Carpenter et al. and Walker et al. (2006). These attributes are latitude, precariousness, resistance, and panarchy. Although these attributes are better known in resilience literature for all systems, recently another set of resilience attributes have been presented by urban studies researchers (Foster, 1993; Godschalk, 2003; Rose, 2011; Winderl, 2015) who have studied the responses of resilient systems to disasters. This set of attributes is more tangible and suitable for the purpose of incorporation into urban indicators since it is based on the study of a resilient system's response to shocks. They indicate that the resilient systems tend to be: redundant, diverse, efficient, autonomous, strong, interdependent, adaptable and collaborative. Below, the properties of resilience in urban contexts have been investigated further:

Redundancy and Durability: such systems have a number of functionally similar components so that the whole system does not fail when one component fails. Planning and design of life safety and critical infrastructure systems should aim for levels of redundancy and durability that are proportionate to the increasing environmental, social and economic stresses related to the impacts of climate change. The redundancy in key infrastructure systems—including fuel supply, waste water processing, electrical power, and, most importantly, food and potable water supply - means that if one of these systems loses its full functionality, there will be enough redundancy in the overall system to fill in the compromised system until it can be substituted or repaired (Godschalk, 2003; Wilkinson, 2012a). This is also applicable to the key life safety systems, such as police, fire and emergency response services. Redundancy seems to be necessary for increasing resilience although it reduces efficiency (Ahern, 2011; Allan & Bryant, 2011b)

Diversity and Density: these systems have a number of functionally different components for protection against various threats. Density, diversity and mix of uses, users, building types, business types, institutions and sources of food and industries increase the resilience of cities since they reduce the potential negative impact to the whole city by the failure of any one particular system. A single use low density residential neighbourhood or a suburban business park are normally under-utilized for long periods of time (Rose, 2004). A vibrant and sufficiently densely populated urban environment, on the other hand, could be well-used and provide tight feedback loops for preparedness and recovery (Allan & Bryant, 2011b).

Efficienct: these systems have a positive ratio of energy and resources supplied to energy and services delivered by a dynamic system. Resilient cities and neighbourhoods have building types and urban forms with reduced servicing costs and reduced environmental footprints. Urban sprawl is extremely expensive to service and maintain – the amount of land, roads, pipes and infrastructure required per capita is disproportionately large. City patterns and built forms that have a reduced footprint on the environment and a reduced burden on municipal resources (e.g. directing growth to where services exist: infill) seem to be more resilient (Ahern, 2011; Godschalk, 2003).

Modular and Independence: such systems have the capability to operate independently of outside control. The importance of consuming local products (including goods, food and energy) and also efficient waste disposal, and water management is not just in decreasing the carbon footprint; it also allows for self-organising and enhances capacity to absorb shocks. Modular system components are more resilient since they have enough independence that damage or failure of one part or component of a system will have a low probability of resulting in failure of other similar or related components in the system. In a modular system, individual modules are relatively autonomous, clearly delineated but connected to their surroundings, and separate from other entities with which they nevertheless interact in some ways (Schilling, 2008). Thus, modular systems are safe-to-fail (Allan & Bryant, 2011). In urban systems, modularity can be exhibited at a variety of scales: in the polycentric pattern of large urban agglomerations (Batty, 2001), in the street blocks of an urban grid (Untermann & Moudon, 1989) and in the construction of lightweight, prefabricated modular buildings. Modularity has even inspired the idea of adaptive cities in the mid-20th century, John Outram, an architect from London, envisaged a city filled with (modular) experimental, impermanent structures which "would adapt in a manner more flexible than any living organism" (Sadler, 2005, p 24).

Robust and Strong: these systems have the power to resist shock or other outside force. The ability of the elements of a system to endure a certain amount of stress or demand without losing function can contribute hugely to the resilience of the system. This attribute of resilience is mostly used in engineering to convey the more narrow static definition of resilience linked to the mitigation of disasters (Pierce et al., 2011). It can be considered as the opposite of vulnerability, however, in some definitions, not being robust does not necessarily lead to vulnerability. The age of the buildings or critical infrastructure, for example, can be considered as a measure of robustness (Khailani & Perera, 2013).

Interdependent and Feedback Sensitive: such system components are linked together so that they support each other. A feedback sensitive system needs to have the ability to spot the changes in its principal elements and respond adequately. The more quickly the response to these detected changes in the system, the better it can cope with stress, and therefore it is more resilient. Social, economic and technical systems designed with tight feedback loops increase resilience (Wilkinson, 2012b). In cities, urban density is one of the important foundations for loop tightness. Density provides for reduced time and costs for moving information and material throughout the system in an efficient and effective manner (Resilient Design Principles, 2012).

Adaptability and Variability: these systems have the capacity to learn from experience and have the flexibility to change. A system exposed to variability allows the evolution of effective and learned adaptive behaviour by learning from previous experience. Cities are already designed to embrace variability to some degree. Engineers design constructed infrastructure with wide design tolerance to encourage a greater range of function (Allan & Bryant 2011), such as streets which are designed to carry variable amounts of storm water depending on the weather. More recently, constructed ecosystems (e.g. swales, rain gardens and wetlands) have been introduced as add-ons to conventional infrastructure to expand tolerance, enhancing the capacity to cope with unpredictable conditions (Bergen et al., 2001). Many cities have been criticized as having conventional, urban infrastructure which is inflexible, designed for efficiency rather than resilience. The approach of many infrastructure designers is to control or reduce disturbance instead of designing to accommodate the risk (Allan & Bryant, 2014).

Innovative and Taking Opportunities: such systems provide multiple opportunities and incentives for broad stakeholder participation. Innovation and experimentation keep a system nimble and responsive. They strengthen a system's capacity to respond to a wide range of unpredictable disturbance, allowing it to "stay in the game" (Pickett et al., 2004, p 373). But experimentation is risky, and success is more likely if the timing, as well as the type of experiment, is aligned with each area's adaptive cycle. Like all open systems, cities and regions constantly cycle through phases of growth, conservation, release and reorganization. This is commonly represented in the transformation of slums to artist's enclaves and then to gentrified suburbs. As a system develops, there is a definite amount of creative chaos (Allan & Bryant, 2011b) followed by a period of steady growth. Ultimately, this creative energy channels into maintaining the status. A significant disturbance at any point in a city's or a region's adaptive cycle can release that energy, and open a window of new opportunities for development of the affected areas and communities. In fact, in the normal course of urban and regional development, physical planning improvements work slowly, as design standards are gradually implemented over many years. A disaster provides the opportunity to implement these changes more quickly. These physical changes also can bring about social and economic improvement. In Mexico City, for example, after the earthquake of 1985, the need to rebuild several medical facilities provided the opportunity to upgrade not only the buildings but the entire medical system (Olshansky, 2005).

Collaborative and Engaged Communities: these systems encourage active participation of community members at all scales, and this can increase the resilience of community. They can be part of delivering the vision to social resilience by choosing to volunteer for emergency actions, by engaging with each other, by generating awareness, by mitigating risks in their own scale and by demanding higher standards (Allan & Bryant, 2011).

2.2.2. Resilience Components

There is a consensus within the research community that resilience is a multifaceted concept comprised of social, economic, institutional, physical and natural/environmental components (Bruneau et al., 2003; Cutter et al., 2008; Gunderson, 2000; Norris et al., 2008; Zhou et al., 2010). Each dimension of community has a particular level of resistance, and a transitioning period and recovery time to bounce back to its previous level or to a higher level of that system's performance (Figure 2.1).

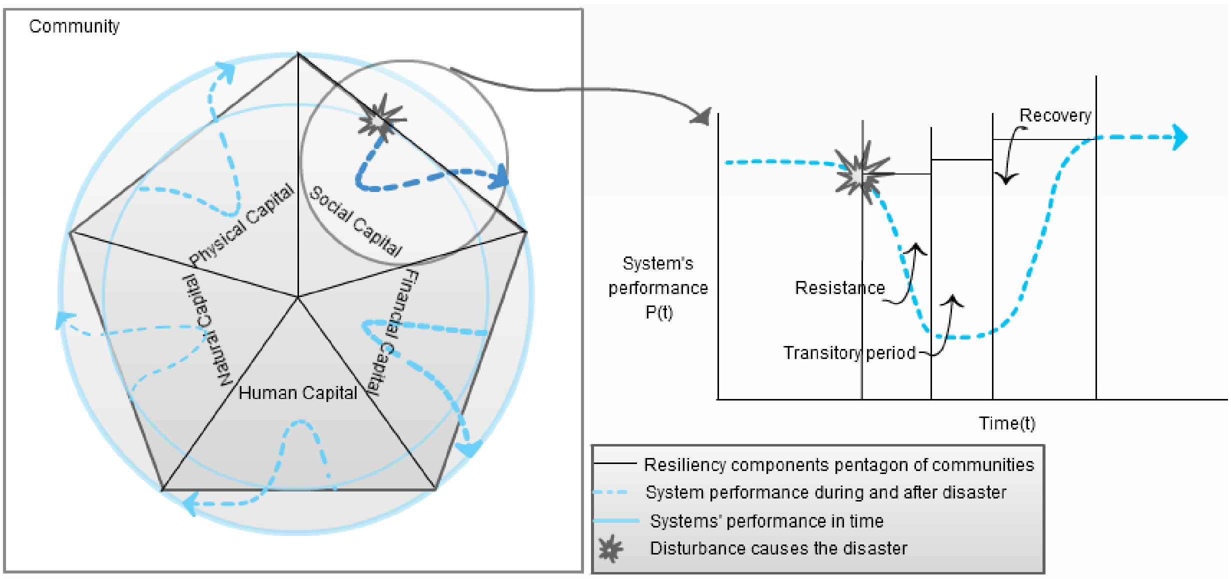


Figure 2.1. A model of disaster resilience models (Irajifar et al. 2013)

A schematic disaster resilience model has been sketched out in Figure 2.1 to show the five types of major disaster resilience components as they have been distinguished in the literature (Irajifar et al., 2013). The circles around the components show the performance level of the system (community) which in the event of a disturbance, falls to a lower level depending on the resistance of the system and the ability of the system to absorb the shock. Each dimension has a particular level of resistance, transitioning period and recovery time to bounce back to the previous level or to an upper level of the system's performance. These characteristics indicate the resilience of the system which may vary from system to system and from one kind of disturbance to another. The response to disturbance in any system depends on different factors in different components of the concept. In this research we aim to find these determinants and the appropriate methods of measuring them. Below, the components of resilience are presented along with a set of the most referred indicators of each dimension.

Economic Resilience

A major contribution to the conceptual definition and measurement of the concept of economic resilience is made by Rose (2004; 2007). He proposed Computable General Equilibrium analysis as a framework for analysing economic resilience to disasters. The framework is applied to the water supply system in Portland (U.S.) and its resilience under simulated disruption is studied using this framework (Pike et al., 2010; Rose, 2004).

The models which have been developed for measuring economic resilience specifically use methods such as input-output, econometric, social accounting, and computable general equilibrium models (Okuyama, 2008). But in a comprehensive model of resilience which includes different dimensions and facades, metrics for measuring economic resilience should be limited to less complicated methods (Chang et al., 2010; Rose, 2004). The ResilUS model, for example, examines two modules of resilience: the impact module and the recovery module. It uses two generic indicators for measuring recovery: the ability to perform and the opportunity to perform. For the economic part, the ability to perform is represented by a business's capacity to be productive, while the opportunity to perform is represented by the demand for a business's product or service (Miles & Chang, 2011).

In a capital based approach to measuring resilience, economic capital basically denotes financial resources that people use to support their livelihoods (Mayunga, 2009; Smith et al., 2001). It contains savings, income, investment or businesses and credit. The economic resources have a straightforward impact on resilience as they show the ability and capacity of a community to absorb the shock of a disaster and accelerate the recovery progress. People with access to financial resources recover more rapidly from disasters (Mileti, 1999). Also access to credit and hazard insurance are associated with the level of household preparedness and ability to take protective measures (Lindell & Prater, 2003). Recovery measures for the economic component, on the other hand, include reopening essential businesses, including banking services and other critical services. UNDP's Economic Vulnerability Index (EVI) has proposed some useful metrics for measuring economic vulnerability in categories as follows: economic and livelihood stabilities, resource equity, economic diversity, economic infrastructure exposure, value of economic assets located in the hazard prone zone and macroeconomic stability (Guillaumont, 2008).

A list of economic metrics in existing resilience models at local level includes direct economic loss and damage, lengths of affected transport routes, microeconomic market efficiency, percent of homeownership, percent of the population who are employed, per capita household income, mean sales volume of businesses, percent of female labour force participation, number of doctors and medical professionals per 1,000 population, lending institutions per 1,000 population, ratio of white to non-white homeowners, retail centres per 1,000 population, ratio of large to small businesses, percent of the population not employed in primary industries (Cutter et al., 2008; Guillaumont, 2008; Heinz, 2000; Mayunga, 2009; Rose, 2004; Rubinoff & Courtney, 2007).

Social Resilience

Social resilience captures the different social capacities of communities in response to external stressors such as a natural hazard, impact or threat. Generally, social capacities are the contextual abilities of individuals and social groups to behave successfully in a certain situation, to overcome negative impacts of a hazard event, and to deploy necessary resources to recover from that event (UNISDR, 2005). Previous studies (Cutter et al., 2010) linking demographic attributes of communities with social capacities suggest that communities with lower levels of minority residents, fewer elderly people, fewer people with disabilities, and fewer people speaking English as a second language, are likely to exhibit greater resilience than communities without these characteristics. Likewise, communities with higher levels of educational attainment, social assistance programs, childcare programs, and vehicle and telephone access demonstrate higher levels of resilience (Mayunga, 2009; Rubinoff & Courtney, 2007). Although social capital has been defined in a variety of ways, there is a common emphasis on certain aspects of social structure, trust, norms and social networks that facilitate collective actions (Green et al., 2002).

In the context of community disaster resilience, social capital reflects social cooperation or community connectedness, which provides an informal safety net during disaster and often helps people to access resources (Cumming et al., 2005; Dynes, 2002; Woolcock et al. 2008). For instance, community ties and networks are beneficial in building disaster resilience because they allow individuals to draw on the social resources in their communities and increase the likelihood that such communities will be able to adequately address their concerns (Dynes, 2002). Similarly, social networks such as friends, relatives and co-workers are important in building disaster resilience because they provide resources that can assist households during disaster response and recovery (Dynes, 2002; Lindell & Prater, 2003); also social bonds have shown to influence the adoption and implementation of hazard adjustment (Mileti, 1999). Furthermore, research has demonstrated that in circumstances where characteristics of social capital or connectedness are lacking in a community, members of that community tend to have less capacity in terms of networks for dealing with disasters (Mathbor, 2007). Social capacity as a form of community cooperation may be measured by a number of variables including religious organizations, voter participation, voluntary associations, non-profit organizations and newspaper readership (Mayunga, 2007). The indicators of social resilience at local level are extracted from SoVI, Cutter's social vulnerability index (Cutter et al.,

2003) and other resilience models (Renschler et al., 2010; Sherrieb et al., 2010) and include: equity, place attachment, social capital (religious or civic involvement), social resources, communication and language competency, transportation access, community health and wellbeing and culture of preparedness.

Environmental Resilience

Environmental resilience focuses on identifying factors that allow natural systems to absorb disturbances and still persist. In this context, resilience is regarded as a process rather than an outcome (Manyena, 2006), which means that environmental resilience is viewed as a system's characteristics and human actions that augment the capacity of the system under stress (Coaffee, 2008; Folke, 2006; Manyena & Gordon, 2015). The environmental component of resilience is concerned with measures of biophysical risk and exposure, the existence of protective resources that guard communities against environmental threats, dimensions of sustainability and also hazard event frequency (Burton, 2012). Variables such as the land area that is not in inundation zones (flood and storm surge), are incorporated to capture risk and exposure within natural systems (Gunderson, 2000). Measures of hazard event frequency are also associated with disaster resilience, since communities adjust to recurring disasters through mechanisms of learning from experience and selective pressure (Gunderson, 2000; Wardekker et al., 2010).

The most referred to indicators of environmental resilience include the amount of land area that is non-developed open space, the presence of windbreaks and environmental planting (Cutter et al., 2008; Mayunga, 2007). Sustainability is also vital for fostering disaster resilience, since human activities are degrading the quality of the environment and the integrity of ecosystems on a daily basis, making current and future populations more vulnerable to hazard events (Cutter et al., 2010; Lindell & Prater, 2003; Renschler et al., 2010).

Institutional Resilience

Institutional resilience is the capacity of communities to predict the unexpected and unexperienced events before they occur and to have a plan for controlling or mitigating them (Gunderson, 2010; Pelling, 2003). The institutional resilience component covers activities and plans that could contribute to risk mitigation and/or disaster preparedness and response (Pelling, 2003; Gunderson, 2010). Planning and mitigation are powerful tools for expecting the unknown, for reducing losses and for facilitating recovery following a hazard impact. Planning and mitigation programs, for instance, reduce potential losses by steering development to the less hazardous areas of the community or by modifying building design to reduce potential losses (Burby et al., 2000). These include a measure of the population covered by a recent hazard mitigation plan, the percentage of the population participating in the Community Rating System for flood, and a measure of households covered by national flood insurance policies (Cutter et al., 2003; Heinz, 2000). Moreover, indicators for assessing rapid urban growth and the number of paid disaster declarations are incorporated as means of gauging institutional effectiveness at managing growth and obtaining disaster relief payouts (Cutter et al., 2008; Mayunga, 2007). Growth management is particularly important in terms of disaster resilience, since areas experiencing rapid growth often lack available high quality housing and social service networks, due to an inability to rapidly adjust to increased pressures (Heinz, 2000; Morrow, 1999). Key indicators for the organizational dimension include the number of available response units and their capacity. In addition to personnel and equipment, organizational resilience also includes elements that measure how organizations manage or respond to disasters, such as organizational structure, capacity, leadership, training and experience (Tierney 2007).

Physical Resilience

Of the five major components of resilience, physical dimension is probably the one which has been the least studied in the literature. Based on the common definition of resilience, physical resilience can be loosely defined as the capability of the built environment to absorb the adverse impacts of the shock on community, maintain its important structure and functions and to quickly restore the affected sites in order to help the community to bounce back to its previous level of function (Mayunga, 2007). However, there is limited discussion in the literature on how this should be measured in a comprehensive model. For example, in the Community Disaster Resilience Framework (CDRF) model (Mayunga, 2007) (explained below), physical resilience is restricted to the physical capital within the community. In the Networked Infrastructure Resilience Assessment (NIRA) model (Mayada, 2011) the focus is just on physical systems networks, and the socio-economic context is not considered in the model.

Resilience can be defined broadly or narrowly. In recent years, increasingly there have been attempts to narrowly evaluate the resilience of individual infrastructure using a complicated engineering and systems approach. Mayada (2011), for example, has developed the Networked Infrastructures Resilience Assessment model (NIRA) which calculates the functionality level of infrastructure during disasters and the time that it takes to return to the previous level of functionality. He applied this model separately to five different networked infrastructure types including transport, telecommunications, maritime transport and an organizational network.

Defining measures of the built environment's resilience in a holistic model needs a different approach. It should provide an overall assessment of the buildings (residential/ commercial/

industrial/ public), lifelines (transport, power, water and communication), infrastructure (roads, bridges, dams and levees), land and building regulations, land use planning and also critical facilities such as hospitals, schools, fire and police stations, nursing homes and emergency shelters (Cutter et al., 2008; Folke, 2006; Godschalk, 2003; Manyena, 2006). Cutter et al. (2008) suggest this assessment needs to include community response capacity (e.g., public safety structures, shelters, health care facilities), and identify critical infrastructure such as pipelines, roads and bridges, water treatment and storage, communications and power transmission. Borden et al. (2007) argue that coastal communities accessible only by a two-lane bridge over the inter-coastal waterway are more vulnerable than those with a number of different access routes. If that bridge is destroyed in a hurricane, for example, the community would remain isolated and dependent on airlifts or boatlifts for vital supplies until such time as alternative access routes could be constructed. If the transportation route in question is a main arterial road, such as the Pacific Motorway, closure of such vital roadways results in interruptions in the movement of goods, people and relief supplies to the affected area, and increases recovery time (Borden et al., 2007).

Physical resilience indicators in existing models also consist of variables for response and recovery capacity (Chang et al., 2010; Cutter et al., 2008; Renschler et al., 2010; Shaw & Team, 2009; Tobin, 1999). Community response capacity is defined in the literature by proxy variables such as the number of police, fire, emergency relief services and temporary shelters per head of population (Chang et al., 2010; Cutter et al., 2008). In addition, response capacity includes the number of principle arterial road and rail miles within a given community. Road and railway infrastructure not only provide a means for pre-event evacuation, they also act as conduits for vital supplies essential for post-disaster response and recovery (Cutter et al., 2010). Moreover, vacant housing units that are rental properties as well as hotels and schools provide response and recovery capacity since they can be utilized as shelters, temporary housing, and as a means of attracting families back to an area following an event (Cutter et al., 2010). The infrastructure resilience component also provides an appraisal of the amount of property that may be particularly vulnerable to catastrophic damage and economic loss (Chang & Shinozuka, 2004; Geis & Kutzmark, 1995). Proxies for vulnerable infrastructure include mobile homes that are particularly susceptible to loss due to their construction type and homes built prior to the enactment of uniform and/or standardized building codes. Metrics for physical recovery might include debris clearance and removal, checking structural integrity of homes and businesses and restoring lifelines (Chang & Shinozuka, 2004; Cutter et al., 2008).

2.3. Disaster Resilience Modelling Approaches

Dynamic relations between people, communities and the natural and built environment make operationalizing of disaster resilience a challenging issue. There are currently a number of theoretical frameworks in the literature proposed which analyse the concept, and, in a number of cases, tools have been developed to measure and compare resilience (Cutter et al., 2008; Mayunga, 2007; Renschler et al., 2010; Rivera & Settembrino, 2010). Most of the resilience frameworks tend to focus on features that reduce risk and increase the ability to recover quickly, and some lean toward only one or a limited number of dimensions which fail to take a broader view of the concept (Mayunga, 2007). This section introduces six slightly overlapping approaches to the development of resilience models that are cited within the disaster resilience literature: a) the capital-based approach (CDRF and CDRI), b) the 4R's approach (the PEOPLES model) c) the place based approach (Disaster Resilience of Place (DROP)) and d) the mitigation and recovery sub-models (the sustainable and resilient community framework, ResilUS)

2.3.1. Capital-based Approach

In recent years major forms of capital (social, economic, physical, environmental and human) have been recognized as being important factors in building community capacities to deal with disasters (Chambers & Conway, 1992; Dynes, 2002; Societies, 2004). The literature suggests that the sustainability and/or resilience of a community depend on its ability to access and utilize the major forms of capital (Beeton, 2006; Societies, 2004). 'Asset pentagon' (Chambers & Conway, 1992) is the core of theoretical framework in the capital-based approach. The resilience models developed by this approach are an extension of the already established social capital approach suggested broadly in the literature (Tierney & Bruneau, 2007) to include the five major forms of capital; social, economic, physical, human, and natural.

CDRF (Community Disaster Resilience Framework)

For the development of the Community Disaster Resilience Framework (CDRF), Peacock et al. (2010) combined an analysis of the capital assets of the sustainable livelihood framework with a focus on the four disaster management phases: preparedness, response, recovery and mitigation. To guide the selection of indicators for measuring the disaster resilience of populations along the U.S. Gulf Coast, the group focused on the intersection between activities and practices associated with the four disaster management phases, and the community capital assets necessary for carrying out the activities and practices associated with each management phase (Figure 2.3). In other words, Peacock et al. (2010) focused their indicator selection on the identification of the capital assets necessary to effectively carry out critical activities associated with each phase. Initially, more than 120 capital indicators were identified, yet following a series of multivariate analyses, the initial dataset was winnowed down to 75 indicators to select indicators that displayed the highest level of internal consistency. The information and communication, as well as the community competence sub-components of resilience, were omitted from the study due to data limitations. The index resulted in the combination of seventeen indicators into a composite index used to measure key elements of economic development and social capital using a sample of 82 counties in the state of Mississippi as their test case.

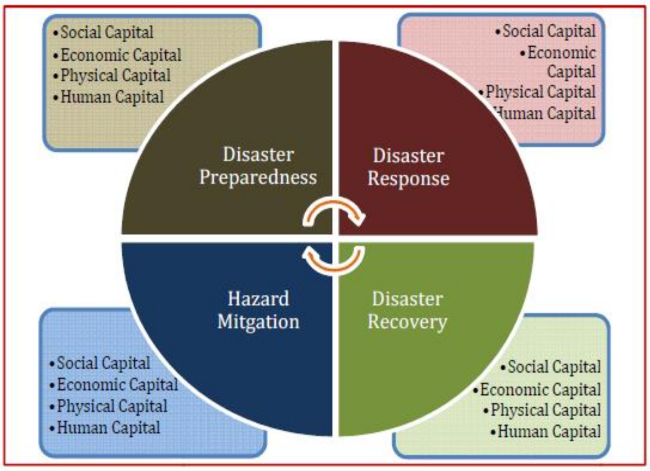


Figure 2.2. CDRF framework
(Mayunga, 2007)

CDRI (Climate Disaster Resilience Index)

Rajib Shaw (2009) and his colleagues at IEDM (the International Environment and Disaster Management Laboratory) have developed CDRI to measure the existing level of climate disaster resilience of their targeted areas in Asia. It is developed based on five resilience dimensions: natural, physical, social, economic and institutional. They adopted a 5_5 matrix to facilitate each dimension with the same weight in CDRI. In each individual city case, resilience information is presented as an overall resilience (a combination of all five dimensions), and also sectoral physical, social, economic and institutional resilience. The overall resilience factor varies between 0 and 10 (Shaw & Team, 2009).

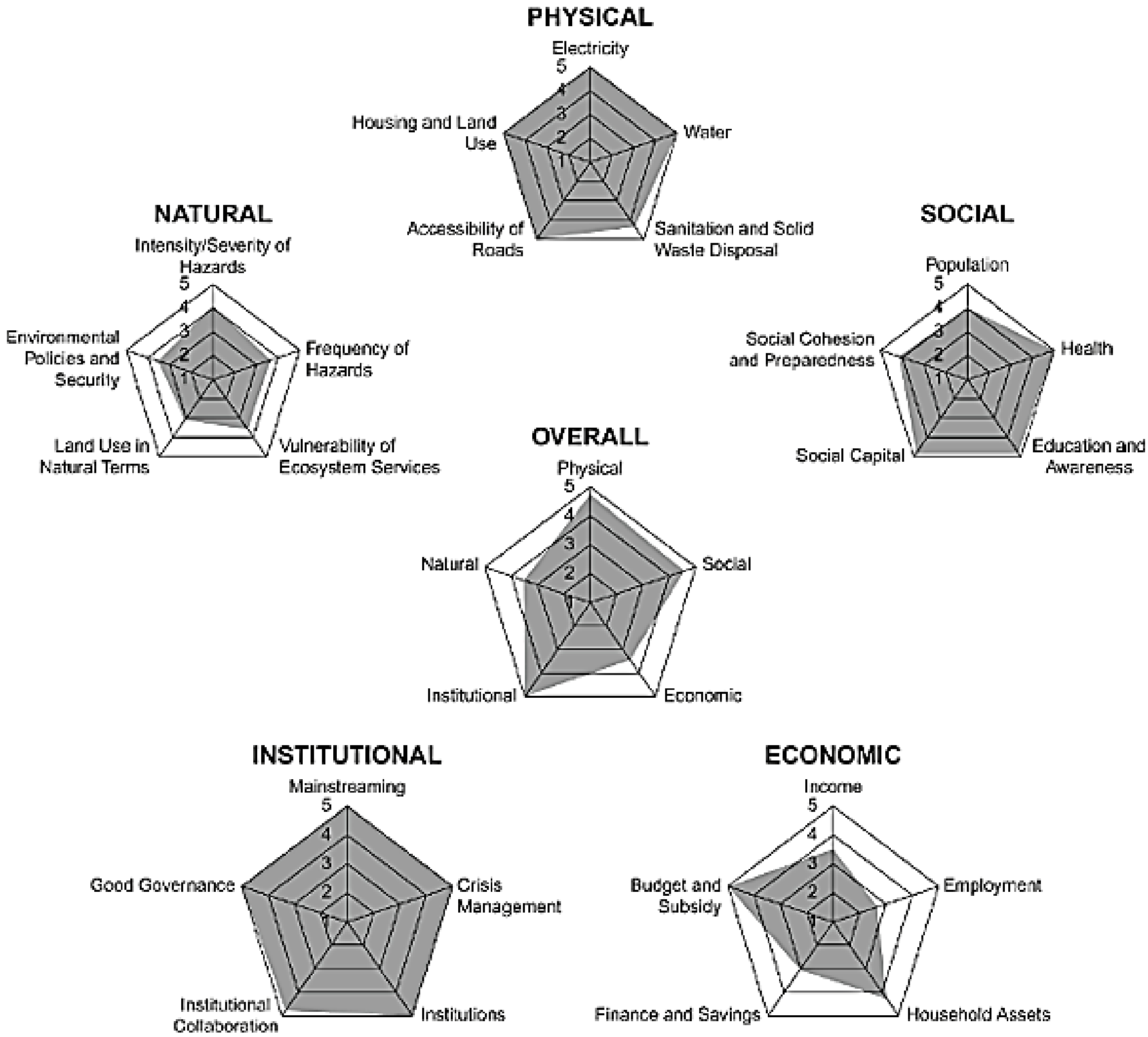


Figure 2.3. CDRI spider diagrams
(Shaw et al., 2009)

2.3.2. 4R's Approach

Researchers have identified a number of characteristics found in resilient systems in which constructed environment and social systems interact. They have pointed out that resilience requires a combination of redundancy and efficiency, diversity and interdependence, strength and flexibility, autonomy and collaboration, and planning and adaptability (Godschalk, 2003; Zimmerman, 2001). Building upon these principles, Bruneau et al. (2003) developed the 4R's concept for resilience modelling which articulates four properties of resilient infrastructures—robustness, rapidity, redundancy and resourcefulness. Robustness refers to the ability or strength of the elements of a system to endure shock without degradation or losing its function. Redundancy shows to what extent the elements of a system are substitutable. Resourcefulness is the capacity of communities to identify problems, establish priorities, and mobilize resources when conditions threaten to disrupt some element of the system. Rapidity shows the extent to which the system has the capacity to prioritise and reach the goals in a timely manner. The 4R's approach highlights multiple paths to resilience where investments can be made to improve all four properties of communities.

PEOPLES

Renschler et al. (2010) in their attempt to establish a holistic framework for measuring disaster resilience of communities at various scales identified seven dimensions of community resilience - "PEOPLES" which stand for: population and demographics, environmental/ecosystem, organized governmental services, physical infrastructure, lifestyle and community competence, economic development and social-cultural capital. The PEOPLES framework suggests a basis to develop other quantitative and qualitative models with a combination of any or each of these seven dimensions to measure the disaster resilience of communities (Renschler et al., 2011).

The PEOPLES model uses a geospatial-temporal distribution within its influence boundaries to define components of functionality. The following diagram describes the dimensions associated with the PEOPLES Resilience Framework and some of their potential indicators.

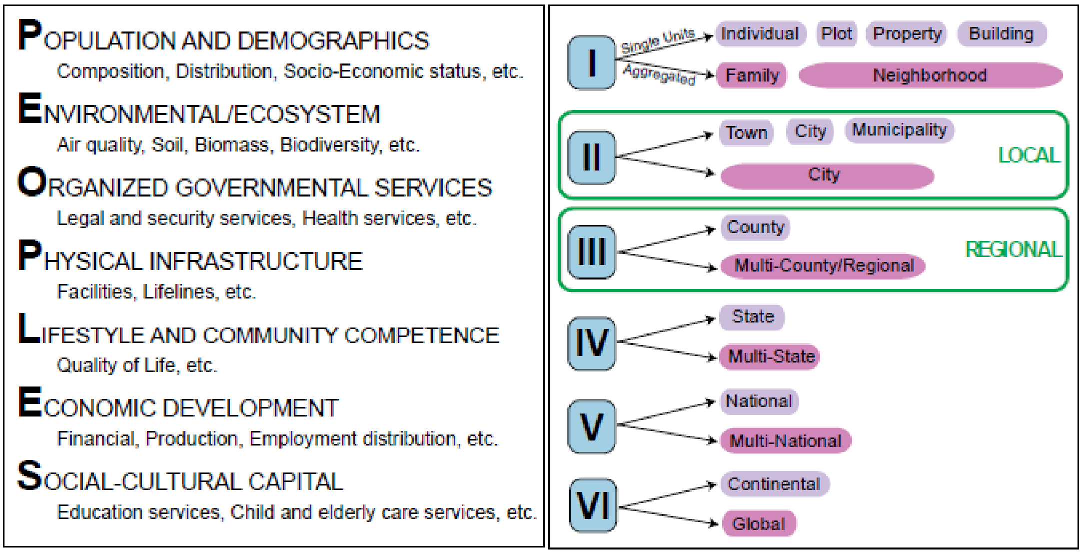


Figure 2.4. PEOPLES resilience framework and associated geographic scales
(Renschler et al., 2010)

The advantage of the PEOPLES Resilience Framework is that it aggregates the dimensions so that they reflect community realities with distinct dimensions and related key indicators (Gilbert, 2010). The developers of this framework aimed to develop a geospatial and temporal decision making support software to facilitate decision making for planners and stakeholders, and to evaluate and increase the resilience of the community (Renschler et al., 2010).

2.3.3. Systems Approach

The Systems approach aims to identify the interactions of different actors or components within certain defined boundaries (Mayada, 2011). Systems' thinking is a methodological approach that provides theoretical and practical tools for understanding and analysing complex real world situations. It is a powerful approach because it enables researchers or observers to think about, describe and understand complex behaviour in simple yet rigorous terms (Gall, 2013; Uday & Marais, 2015). The tools utilised in a systems thinking approach facilitate understanding and modelling system processes and feedback dynamics. This approach has been used in the development of Systems Diagrams and the Networked Infrastructure Resilience Assessment (NIRA).

Resilience is frequently described as a 'system' or a 'system of systems'. A systems approach usually refers to a view of resilience as a self-regulating system – or cluster of systems - that are self-correcting through feedback. This has implications for measuring disaster resilience: a system-wide approach to resilience needs to capture 'a range of activities, actors and processes (Cimellaro et al., 2011). Having said this, Gall (2013) argues that a coherent systems approach has yet to materialize, despite recent attempts to develop one. For example, a scoping study by the OECD looked at the various components of a resilient system and how to measure it (Mitchell, 2013). The Network of Adaptive Capacities understands community resilience as a process – not as an outcome - linking a network of adaptive capacities to adaptation after a disaster. The DFID/TANGO model looks at food security resilience through a systems lens, but without defining detailed indicators (Frankenberger et al., 2012).

NIRA (Networked Infrastructure Resilience Assessment)

The NIRA was developed by Omer Mayada at Stevens Institute of Technology during his PhD studies and was later applied to five different urban infrastructure networks including: telecommunication, transportation, maritime transportation and organizational networks. This framework proposes that the resilience of the systems can be measured quantitatively by assessing the impact of disruptions on the performance measures of the system. The framework involves a series of steps that include identification of system's boundary, assessment of a system's resilience metrics, and identification and evaluation of appropriate resilience-enabling schemes (Mayada, 2011).

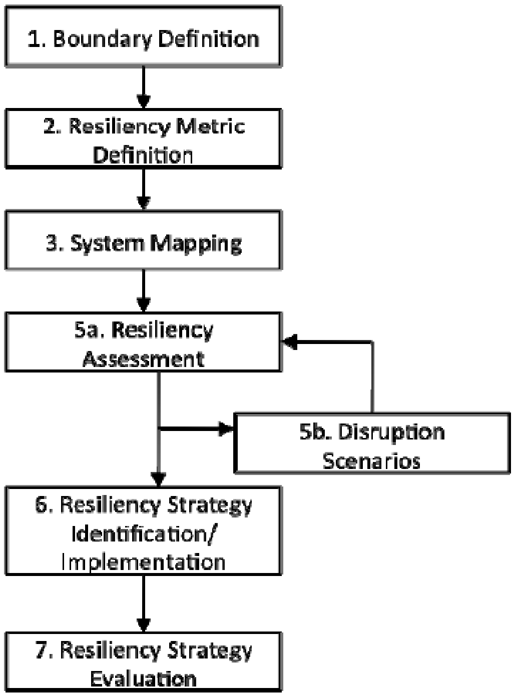


Figure 2.5. Networked Infrastructure Resilience Assessment (NIRA) framework
(Mayada, 2011)

Systems Diagram

Bruneau et al. (2003) developed a framework to quantitatively assess disaster resilience based on systems science. The keys to this framework are: reduced failure probabilities, reduced consequences from failures, and reduced time to recovery. They are also known as the 4R's that intersect with the four dimensions of resilience (TOSE): technical, organizational, social and economic (Bruneau et al., 2003).

The Systems Diagram is organized in three horizontal layers (Figure 2.6). The bottom layer is representative of the situation where no intervention is made on the existing systems; earthquakes occur, impact the systems (e.g., infrastructure), and disasters ensue. The middle layer consists of the first level of actions and decisions, in which decisions are made based on simple initiatives such as rapid intervention. On the top level, multi-attribute information is collected and used for decision making. This general framework is equally applicable to individual systems, combinations of systems and communities. The figure below illustrates the basic concepts embedded in this framework (Bruneau et al., 2003).

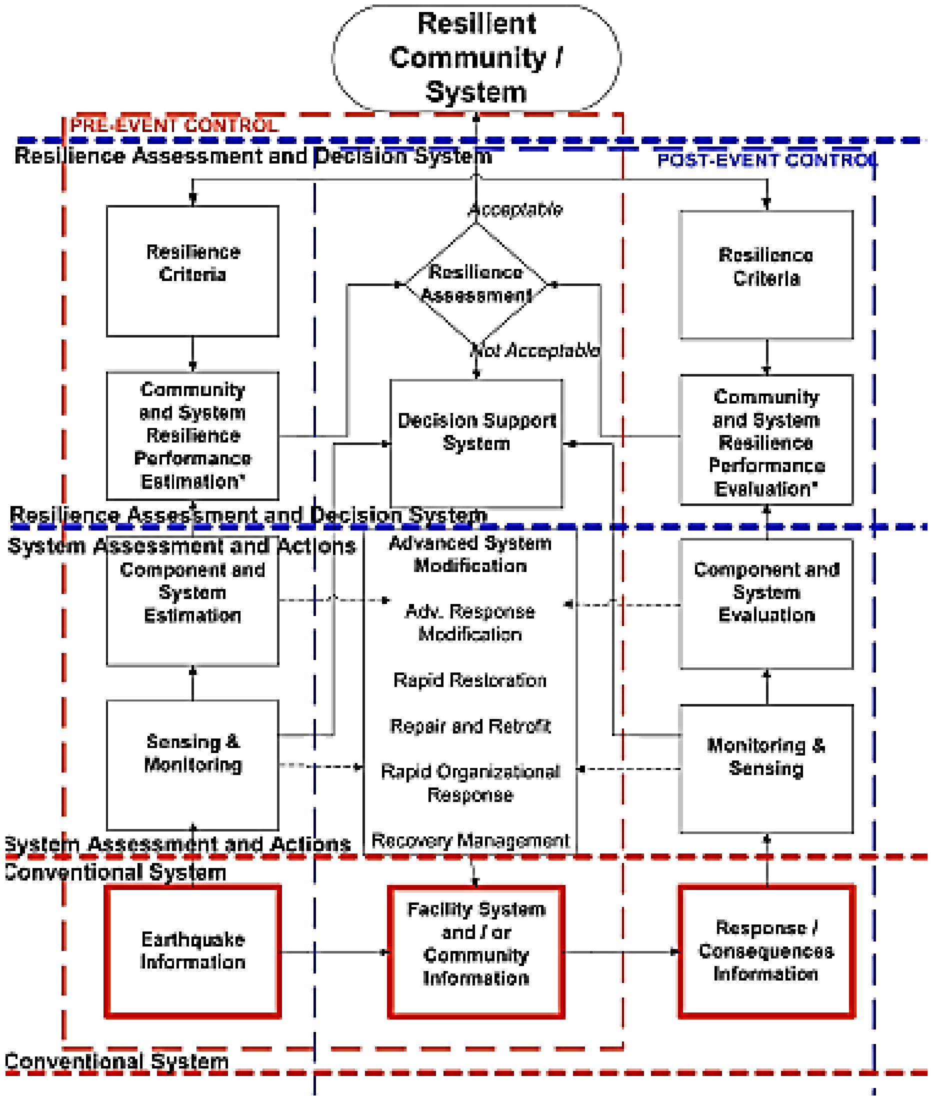


Figure 2.6. Systems Diagram, schematic level of details

(Bruneau et al., 2003)

URF (Urban Resilience Framework)

The Urban Resilience Framework (URF) has been developed by Arup Resilience Consulting and ISET (Institute for Social Environmental Transition). The key elements of the URF are urban systems and social agents. Urban systems include ecosystems, infrastructure systems, institutions and knowledge. One or more of these systems, or the linkages between them, may have critical weaknesses or fragilities with respect to climate impacts (Tyler et al., 2010). The framework also emphases the behaviour and the socio-economic situation of internal agents (governmental organizations, private businesses, identity groups, households and individuals) of which urban populations are composed, their ability to access urban systems and services, and the strategic responses in time of stress (da Silva et al., 2010).

The framework, however, is practical as an urban resilience planning guide. It achieves this by focusing on the fragility of basic urban systems (water, power, transport, communication, etc.) and their exposure to climate change, the socioeconomic marginality of groups, the role of different agents (government departments, the private sector, communities, etc.), and the way common institutions (codes, tenure rights, etc.) shape what can be done (Tyler et al., 2010).

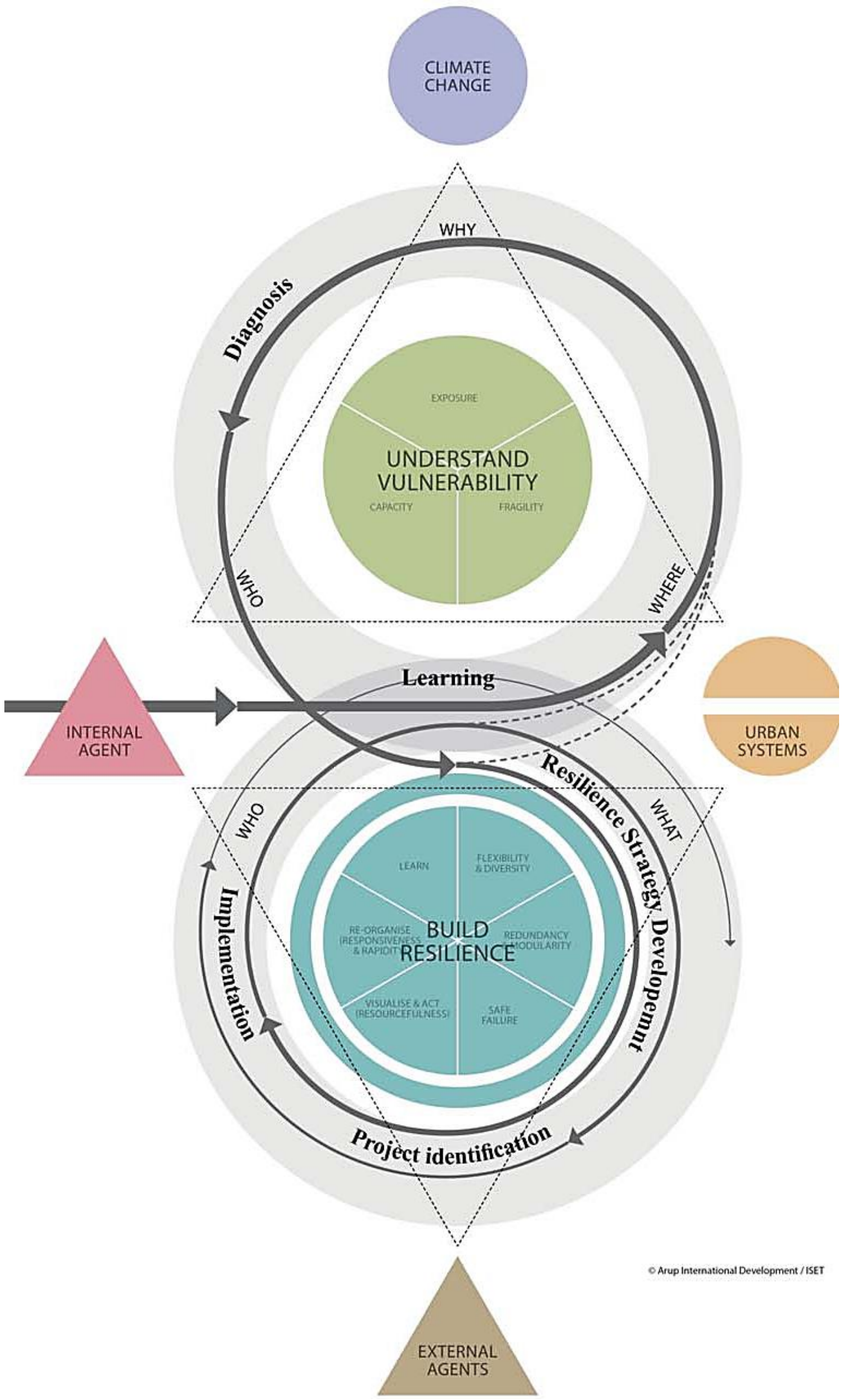


Figure 2.7 Urban Resilience Frameworks
(Tyler et al., 2010)

2.3.4. Place-based Approach

The place-based approach locates local vulnerability within the larger contexts that influence it; however, it may fail to clearly differentiate between exposure and sensitivity and also does not include a temporal dimension that shows where vulnerability begins and ends. The value of the place-based framework is that it explicitly focuses on a community's antecedent conditions. The antecedent conditions are a product of processes within communities that are place specific and occur within and between natural systems, social systems and built environments. A community's antecedent conditions may therefore be analysed in conjunction with coping responses to determine a given recovery potential (Burton, 2012).

DROP (Disaster Resilience of Place)

Cutter et al. (2008) developed what they call a disaster resilience of place model (DROP) (see Figure 2.8). In a nutshell, the DROP model has two main components. The first component consists of the antecedent conditions (the inherent vulnerability and inherent resilience) which are the product of the interactions of the social, natural and built environment systems. Hazard impacts are the results of the antecedent conditions, hazard events, and the ability to cope and respond. The second component consists of the actions necessary to deal with disaster impacts, which include hazard mitigation, disaster preparedness, disaster response and disaster recovery. As of 2015 the DROP model was still under development, however there is currently not much discussion of how the model will be operationalized, despite the fact that it has been benchmarked for counties within the U.S. Federal Emergency Management Agency's (FEMA) Region IV (Cutter et al., 2010). Moreover, via personal contact with Susan Cutter (21.07.2012), it has been confirmed that the DROP model is now being validated in a case study of the Mississippi Gulf Coast.

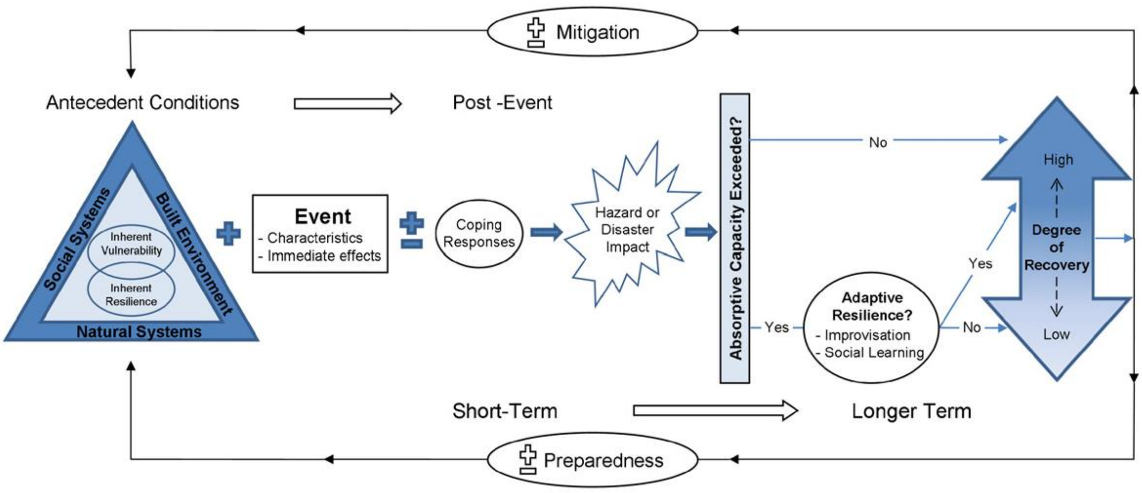


Figure 2.8. Disaster Resilience of Place Model

(Cutter et al., 2008)

DRLRL model (Disaster Resilience of Loss Response of Location)

Zhou et al. (2010) developed a place-based model called Disaster Resilience of 'Loss-Response' of Location (DRLRL). In this model, disaster resilience is defined as "the capacity of hazard affected bodies (HABs) to resist loss during disaster and to regenerate and reorganize after disaster in a specific area in a given period" (Zhou et al., 2010, p. 28). DRLRL shows the loss potential and the biophysical /social response of the place, as shown in the figure below. In DRLRL's conceptual framework, there is an emphasis on locality as it forms the ultimate unit of analysis for assessing disaster resilience. According to the definition of resilience in this model, losses can be decreased with appropriate resistance or increased by a poor resistance (Figure2.9). Loss potential in the DRLRL is filtered through the social fabric (e.g., ability to respond) and geographic context (geographic setting) to determine biophysical and social resilience to find the resilience of location. Therefore, this model assumes that adaptation to geographical setting, including hazard risk, social–economic structure and local culture can increase the resilience of location in spite of the characteristics of hazard varied including frequency, intensity, duration, return period, area covered.

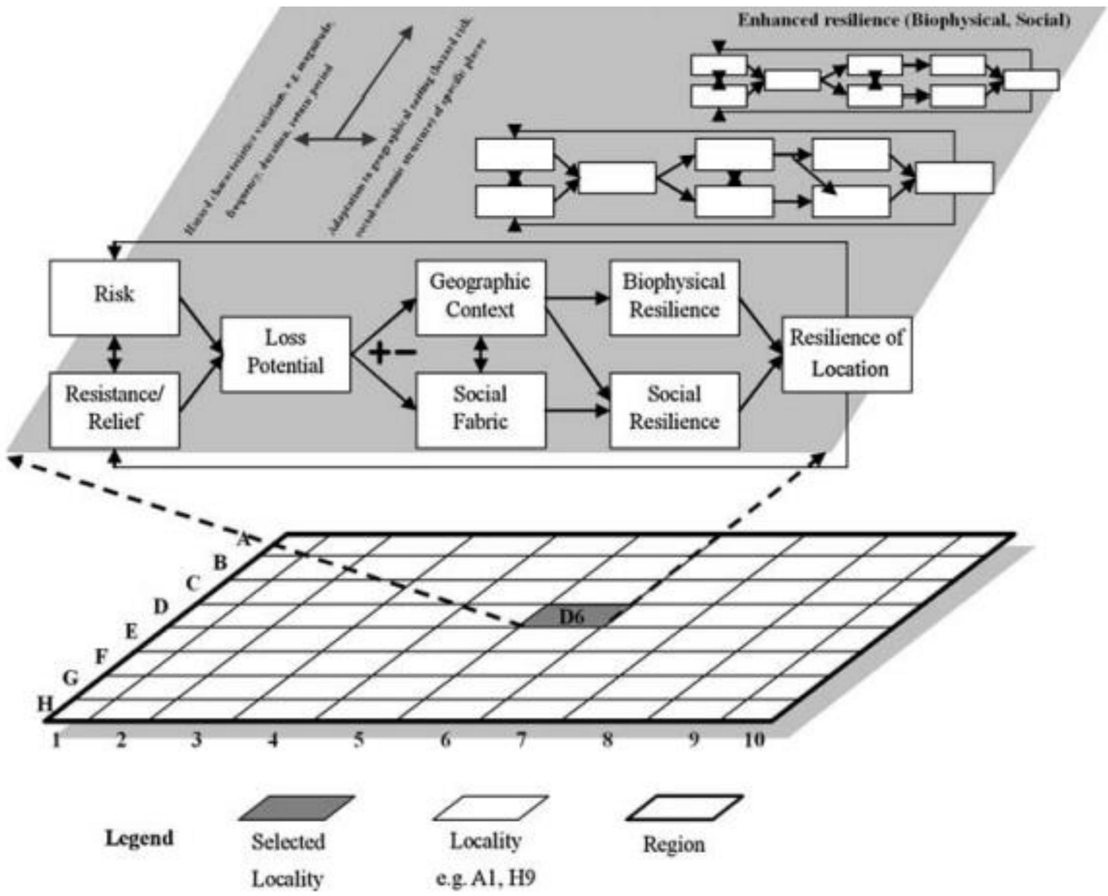


Figure 2.9. Model of disaster resilience of "Loss Response" of location (DRLRL)
(Zhou et al., 2010)

2.3.5. Frameworks with Mitigation and Recovery Sub-models

In this approach, the main model is structured based on the different modules in a definition of resilience. The ability to absorb the shock can be assessed by an impact assessment model and the capability to recover quickly after disaster can be evaluated by a recovery model. The ResilUS model and the sustainable and resilient community framework have been developed by this approach.

ResilUS

Miles and Chang (2008) developed a simulation model called ResilUS that tries to operationalize community resilience across multiple, hierarchical scales— household/business, neighbourhood and community—in relation to a range of policy and decision variables associated with each scale. The ResiUS model assesses resilience through measuring the functionality of an infrastructure system after a disaster and also by the time it takes for a system to bounce back to its previous levels of performance (Miles & Chang, 2008).

The ResilUS model explicitly represents damage associated with a hazard event to three elements of community capital: the physical, economics, and personal (i.e., health). It relies on two generic indicators of recovery: 1) the ability to perform, and 2) the opportunity to perform. These recovery indicators are specifically represented by multiple variables in ResilUS. For example, a household's ability to perform can be measured by health, and businesses can be measured by their capacity to be productive. Opportunity to perform for households is measured by employment level and for businesses by demand for their products or services (Miles & Chang, 2011).

Sustainable and Resilient Community Framework

Tobin (1999) offered a framework in which sustainable and resilient communities can be assessed. The framework includes three theoretical models which can be employed to operationalize the concept of sustainability and community disaster resilience. These models are: (i) the mitigation model, (ii) the recovery model, and (iii) the structural cognitive model.

Tobin (1999) suggested a comprehensive planning approach which includes mitigation programs to reduce risk and exposure to hazards. It also considers post-disaster plans that help short and long term recovery after disasters. Furthermore, structural and cognitive factors are included in this model as they can effectively influence programs related to building sustainable and resilient communities.

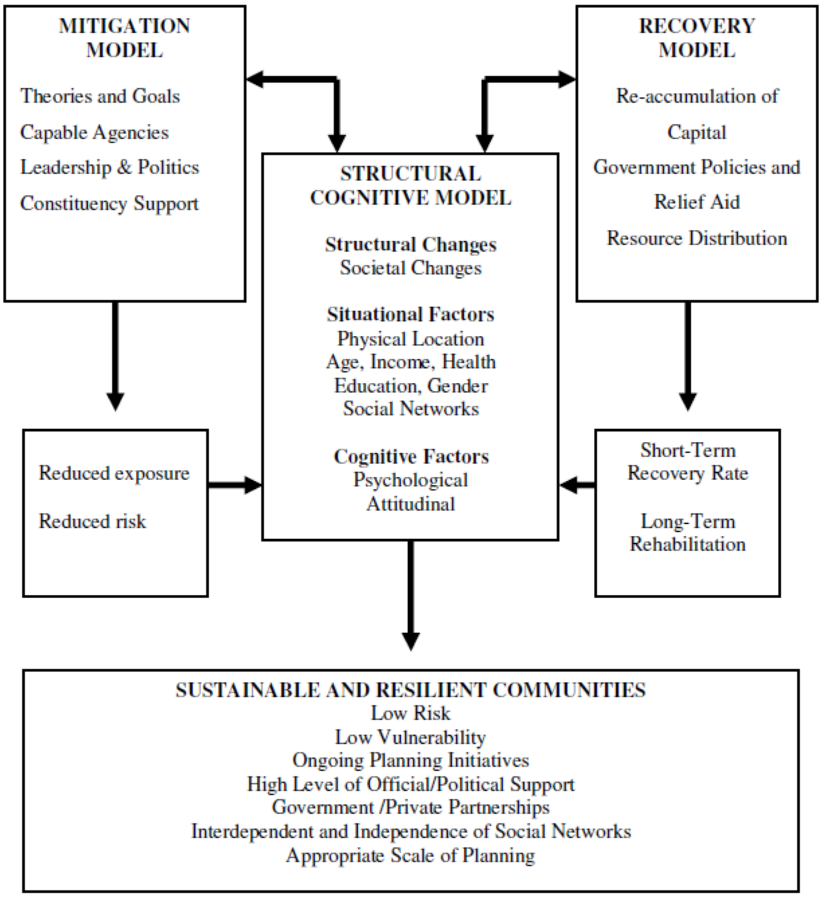


Figure 2.10. Sustainable and resilient community framework
(Tobin, 1999)

2.4. Critical Analysis of Resilience Modelling Approaches

The properties of the discussed models are evaluated below based on a range of criteria to identify the gaps in the literature based on the characteristics of resilience models. The evaluation criteria are extracted from the literature on assessments of urban models (Wegener, 1994) and include: comprehensiveness, structure and indicator building methods, scale and unit of analysis, dynamic, data requirements, validation and operationality, and actual and potential applications. Table 2.4 shows a summary of the analysis of the eight models discussed.

2.4.1. Comprehensiveness

The comprehensiveness of disaster resilience models can be assessed based on:

1. The dimensions of resilience included in the models such as built environment, economic, social and organizational resilience.
2. The temporal phases of disaster discussed in the model such as mitigation, preparedness, response, and recovery.
3. The types of disasters covered by the model such as geological, climatic, etc.

Table 2.3 notes that the PEOPLES model stands for seven dimensions of disaster resilience: population and demographics, environmental, organized governmental services, physical infrastructure, lifestyle and community competence, economic development, and social-cultural capital. As the third column of Table 2.3 shows, DROP, CDRF and CDRI consist of five dimensions of the aforementioned asset pentagon, but DROP and CDRF disregard the environmental resilience on purpose due to complexity or data inconsistence and relevance (Mayunga, 2009). The DROP, PEOPLES, ResilUS, CDRF and the Systems Diagram models are comprehensive in the sense that they address at least four dimensions of resilience. They all encompass the technical, social, economic and organizational dimensions. The NIRA focuses on the technical dimension of urban networked infrastructure. All of the models except the Systems Diagram and the URF are multi hazard models, whereas the Systems Diagram is a seismic specific model, and the URF has been developed basically for climate change resilience and thus does not consider the risk as an abrupt change to urban systems but a slow onset challenge. All of the models consider the pre and post disaster conditions but only the CDRF specifically emphasizes the preparedness and response phases, which are neglected by the others (Mayunga, 2009).

2.4.2. Structure and Indicator Building Methods

A proper resilience index should identify the distinct dimensions and related key indicators and also aggregate the dimensions in ways that reflect community realities (Burton, 2012). The PEOPLES model is the most successful model in this respect. The advantage of the PEOPLES model is that it aggregates dimensions to reflect community realities with distinct dimensions and related key indicators (Gilbert, 2010). It uses a geospatial-temporal distribution within its influence boundaries to define components of functionality. Interdependencies between and among these components are key in determining the resilience of communities (Renschler et al., 2010). The physical infrastructure dimension in the PEOPLES model includes both facilities and lifelines. Facilities include housing, commercial facilities and cultural facilities, while the lifelines category includes food supply, health care, utilities, transportation and communication networks (Renschler et al., 2010). In the physical dimension, historical and continuously gathered information through remote sensing and Geographic Information Systems (GIS) plays a major role in assessing the resilience of all integrated systems and feeds a predictive resilience model (Renschler et al., 2010).

Table 2.3. Summary of the resilience model properties

Disaster resilience model	Developer/ Affiliation	Components	Scale/Unit of analysis	Methodology	Data sources	Application
DROP Disaster Resilience Of Place	Cutter et al. HVI- University of South Carolina/ 2008	Social Technical Economic Organizational	community/ county	Spatial mapping; Weighting; aggregation; Multivariate analysis; Sensitivity Analysis	Census; American community survey	Information gathering Comparison of the resilience of different counties
PEOPLES MCEER's resilience framework	Renschler et al. MCEER- University at Buffalo/ 2010	Population &demographics Environment Organized governmental services Physical infrastructures Lifestyle & community competence Economic development Social cultural capital	Community (can be adapted to multi scale)/county	Spatial (time dependant community functionality maps); Visual inspection of RS imagery; quantitative and qualitative models for any or a combination of dimensions. E.g. SoVI for social resilience, NDVI for environmental resilience and etc.	Census ; Quality of life surveys; Utility usage; Mortgage rate; Voter registration; Home price indices; Unemployment rates; SEC filings; Content Ground trothing interviews; pre/post disaster detection analysis; Object oriented classification; change detection analysis	Information gathering; Comparison of resilience between Counties; Empowerment of people; After complete development, it can be used as a geospatial and temporal decision support software tool
Systems Diagram Quantitative framework for seismic resilience assessment	Bruneau et al. MCEER- University at Buffalo/ 2003	Conventional systems System assessment and actions Resilience assessment	Community level, infrastructure networks	Scenario based resilience assessments	---	---
ResilUS A community-based disaster resilience Model (Miles and Chang, 2011)	Miles & Chang et al. University of British Columbia & MCEER/ 2007	Recovery module Loss estimation module	City/ Scalable to any number of neighbourhoods or agents/PUMA (Public Use Microdata Areas)	Spatial; probabilistic methods; Spread sheet- based Fragility Curves to model loss; Markov chain to model recovery	Poll results; general observations from previous studies; Zip Code Business Pattern data; Surveys from previous studies; some simulated data; USGS shake map data	Information gathering; education, training, public awareness; Resilience Comparison between different
CDRF Community Disaster Resilience Framework (Mayunga, 2007)	Joseph Mayunga HRRC - Texas A&M University/ 2009	Human Capital Social Capital Economic Capital Physical Capital	Regional/ County	Spatial; GIS based Composite indicators; Correlational analysis; Regression analysis; Incremental validity	Census, Insurance datasets; County business patterns; Spatial Hazard Events and Losses database for US (SHELDUS); US Fire administration;; Centre for Disease control and prevention(CDC)	Information gathering; Enhance local community coping capacity; comparing disaster resilience of communities; operationalize the disaster resilience concept to support planning, management and decision making
CDRI Climate Disaster Resilience Index (Shaw, 2009)	Rajib Shaw "Human Security Engineering for Asian Megacity" of Kyoto University/ 2009	Physical Social Economic Institutional Natural	City	Non spatial; Spreadsheet – based; Questionnaire survey	Surveys; Secondary data	Information gathering; Priority setting and policy recommendations based on level of resilience in each dimension;
URF Urban Resilience Framework **(Tyler et al., 2010)**	StephenTyler Marcus Moenc Jo da Silva ARUP + ISET/ 2009	Urban Systems (ecosystem, infrastructure, institutions, knowledge) Social agents	City/ Wards (communes)	Shared Learning Dialogues(SLD) workshops; GIS enabled sampling and aggregation method; Hazard, Capacity and Vulnerability Assessment(HCVA)	Identification of homogeneous socio-economic clusters by satellite imagery verified with rapid ground surveys; Secondary data	Information gathering; Interpretation; Collaboration; implementation
NIRA Networked Infrastructure Resilience Assessment (Mayada, 2010)	Omer, Mayada Stevens/Institute of Technology/ 2010	Urban Network Systems	Infrastructure networks	Non spatial; Spread sheet-based; System mapping; Network flow analysis; Disruption scenarios	State of New York department of Transportation; Highway capacity manual	Resilience assessment; Resilience strategy evaluation

In the DROP model, two main qualities are considered for the resilience of communities: inherent (functions well during non-crisis periods); and adaptive (flexibility in response during and after disasters). Cutter's social vulnerability index, the SoVI, in the DROP model has been used in the PEOPLES model to measure the social dimension of resilience. The SoVI model integrates exposure to hazards with the social conditions that make people vulnerable, including socio-economic status, the composition of the population (elderly and children), development density, rural agriculture, race, gender, ethnicity, infrastructure employment and county debt/revenue (Cutter, 1996; Cutter et al., 2003). ''Community competence'' metrics are also considered in the PEOPLES index which represents how well a community functions pre-and post-disaster, including sense of community and ideals, as well as attachment to place and desire to preserve pre-disaster cultural norms and icons (Gilbert, 2010). Disaster-specific indicators account for the comprehensiveness of community warning plans and procedures, and the extensiveness of citizen and organizational disaster training programs (Tierney, 2009). Metrics for measuring economic resilience have classically employed loss estimation models to measure the property loss and the effects of business disruption after disasters (Chang, 2010; Rose, 2004). The PEOPLES model, on the other hand, assesses both current economic activities and dynamic growth economic development (Renschler et al., 2010). The ResilUS model uses probabilistic methods. Each model in the ResilUS is calculated through a comparison between a uniform random number and aggregation of all input variables which are stated as probabilities (e.g., the probability of a restored water service in a neighbourhood). The recovery modelling has employed the Markov chain, while MATLAB/ Simulink and fragility curves are used for loss estimation (Miles & Chang, 2011). All dimensions in the Climatic Disaster Resilience Index (CDRI) consist of a number of parameters and each parameter has a number of complex or simple variables. These variables are in fact the indicators to assess the climate disaster resilience of an urban community. A total of 23 indicators represent the resilience in the CDRI including: 8 indicators for the physical dimension, 2 indicators for the natural dimension, 6 indicators for the economic dimension, 4 indicators for the social dimension and 4 indicators for the institutional dimension. The total number of indicators for disaster resilience in the CDRF reaches 75, representing its four capital domains: social capital (9), economic capital (6), physical capital (35), and human capital (25). The overall CDRF scores are calculated using the average method, which is based on equal weighting of sub-indices and provides better results than the summation method (Bruneau et al., 2003; Mayunga, 2007). Table 2.3 summarizes the main properties of the models discussed above.

2.4.3. Scale and Unit of Analysis

Disaster resilience is often allocated to technological units and social systems. On smaller scales, such as when critical infrastructure is considered, the focus is mainly on technological aspects. On greater scales when the whole community is considered, the scope is expanded to include the interaction of multiple systems – human, environmental, and others which together add up to ensure the resilience of a community (Renschler et al., 2010). As column 4 of Table 2.3 shows, with the exception of the NIRA, which is the only model focused on networked infrastructure, all seven models are at community level (Mayada, 2011). The Systems Diagram, for example, is developed for community level resilience assessment and also for infrastructure networks systems.

At the community level, the human component is central, because in the case of a major disruptive event, resilience depends first on the actions of people operating at the individual and neighbourhood scale (Manyena & Gordon, 2015). Community resilience also depends heavily on the actions of different levels of government, and its agencies at the local and regional levels, when a disruptive extreme event occurs. The PEOPLES model is based on basic community organizational units at a local (neighbourhoods, villages, towns or cities) and regional (counties/parishes, regions or states) level. Thus it can be considered as a multi scale model similar to the ResilUS model which is scalable to any number of neighbourhoods or socio economic agents and communities. Among these community level models, the URF and the CDRI use the city as their unit of assessment while the DROP and the CDRF models' unit of analysis is the county. The county level is chosen for these models as a reasonable unit of analysis mainly because of ease of availability of data and because it is where hazard mitigation plans and risk reduction programs are directed in the US (Mayunga, 2007). The review of resilience models suggests that although resilience operates at different scales, local resilience has been ignored by current resilience measurement models, whereas the local level is mostly the focus of hazard mitigation and preparedness plans (Campanella, 2006; National Emergency Management Committee, 2009; Wallace & Wallace, 2008).

2.4.4. Dynamics

Resilience can be considered as a dynamic quantity that changes over time and across space. The conditions defining resilience are dynamic and ultimately change with differences in spatial, social and temporal scales (Renschler et al., 2010). A society is deemed as being resilient to environmental hazards at a one time scale (e.g. a short-term phenomenon such as a severe weather event) due to mitigation measures that have been adopted, but not another (e.g. a long-term event such as climate change). The temporal scale at which resilience is measured is an important issue since it affects the selection of variables and parameters in index construction. Although resilience is a dynamic process, for measurement purposes, it is often viewed as a static phenomenon (Cutter et al., 2008).

In all eight models, there are signs which indicate the dynamic or quasi dynamic nature of the models. For example, the post-event processes embedded within the DROP model allow the conceptualization to be dynamic, yet the antecedent conditions can be viewed as a snapshot in time or as a static state (Cutter, Barnes et al., 2008). In the PEOPLES model, community resilience indices are integral of the geospatial – temporal functionality of components of resilience. The PEOPLES model is supposed to continuously measure and monitor the functionality of the systems over time (Renschler et al., 2010). The closed loops in the Systems Diagram and the iterative processes of diagnosing vulnerability, planning and implementation indicate the requirement for an iterative dynamic process to achieve a higher level of resilience in systems (Bruneau et al., 2003). The dynamic of the ResilUs model is represented by pre/co-event and post-event models. For a particular dynamic (time-based) output, each model state is calculated as a comparison between a uniform random number and the aggregation of all input variables (Miles & Chang, 2011).

2.4.5. Data Requirement

Researchers often have difficulties in gathering data on resilience indictors for input into their models (Cutter et al., 2008). Availability and accessibility of the data has been one of the most important criterions for indicator construction (Mayunga, 2009). In general, data for these models fall into four types: case studies, insurance claims, direct measurements and survey methods (Gilbert, 2010). A huge part of the data for these models, particularly in the DROP, URF, CDRF and CDRI models primarily comes from the secondary datasets such as the census (Cutter et al., 2008; Mayunga, 2007; Shaw & Team, 2009; Tyler et al., 2010). The PEOPLES Resilience Framework requires the combination of qualitative (such as pre/post disaster detection analysis; object oriented classification; change detection analysis of the remote sensing imagery) and quantitative data sources at various temporal and spatial scales (such as voters' registration, mortgage rates, saving rates, court reports, crime reports), and as a result, information must be aggregated or disaggregated to match the scales of the resilience model and the scales of interest for the model's output (Renschler et al., 2010). In the ResilUS model, because of the large number of model variables and their interrelationships, the behaviour of this model is complex and it needs more simulated, aggregated and micro-data in addition to census data. However, its modularity helps to substitute a data source for a model reference. For example, rather than modelling lifeline restoration, actual lifeline restoration time-series data can be used (Bruneau et al., 2003).

2.4.6. Validation and Operationality

Many researchers, in developing composite indexes in resilience studies, fail to empirically validate the measures especially in terms of incremental validity (Renschler, 2013; Schipper & Langston, 2015; Vincent, 2004). This is one of the major flaws of using composite indexes, as there is no simple way to get scientific validation of a particular index (Davidson & Shah, 1997). The absence of validation is a major concern. In many circumstances, the index relies on empirical data that is far from perfect. It has been assumed by some scholars that because numbers have been derived using basic statistical procedure, the overall results of the index are valid and reliable (Simpson & Katirai, 2006). However, some qualitative methods such as in-depth surveys and case studies can be used to validate the index. The literature argues that the best way that any sort of metrics related to the disaster field could be validated would be to frequently test them after major events and improve them accordingly. This would take a considerable amount of time (Simpson & Katirai, 2006). Chang and Miles, for example, have made several attempts to validate the ResilUS model (Chang et al., 2010; Miles & Chang, 2008). The ResilUS model has been applied for modelling the recovery of Kobe after the 1995 earthquake and also the 1994 Northridge earthquake disaster in order to calibrate several output variables with empirical data. The ResilUS model is currently being developed to better represent socio-cultural, personal and environmental capital to assist in modelling the resilience of the Gulf Coast area of Louisiana in association with the 2005 Hurricane Rita disaster (Miles & Chang, 2008). The NIRA, CDRI and the URF models have not been scientifically validated. However, the NIRA has been applied to four types of critical infrastructure systems. These case studies probe the resilience of the studied infrastructure systems in the face of specific disruptive events: telecommunication, transportation, maritime transportation and organizational networks. The CDRI and the URF have been applied to 10 Asian cities to measure their resilience and to provide some policy recommendations based on their expected level of resilience (da Silva et al., 2010; Shaw & Team, 2009). Among all models, the CDRF as a PhD project has undergone a full internal model validation process for its content by construct validity, predictive validity and reliability validity, and plausible results were obtained (Mayunga, 2007). Based on an email contact [23.07.2012], Cutter et al. are validating the DROP model through a case study from the Mississippi Gulf Coast. The PEOPLES model has been partially applied to the 2010 Haiti earthquake disaster (Renschler, 2013).

2.4.7. Actual and Potential Applications

The spectrum of applications which can be addressed with these eight frameworks is very narrow, considering the range of issues facing communities in terms of their resilience in the event of disasters. These issues can be categorized into two major groups, - loss reduction and quick recovery after disaster (Gilbert, 2010). However the frameworks can be utilized to assess the strategies, actions and policies for loss reduction and recovery catalyzing by developing different scenarios.

The PEOPLES, the CDRF, the DROP and the CDRI models have the potential to compare communities with one another in terms of their resilience, by quantifying the disaster resilience and generating hotspot maps or diagrams. They all have the capacity to incorporate temporal dimension to determine whether individual communities are moving in the direction of becoming more resilient in the face of various hazards, and in general, to show how the concept of disaster resilience can be used to enhance the disaster planning and management procedure (Cutter et al., 2008; Mayunga, 2007; Renschler et al., 2010; Shaw & Team, 2009). However, in the ResilUS model, limitations such as lack of verification and validation make it more appropriate for education, training and public awareness purposes rather than for actual planning purposes (Miles & Chang, 2011). The URF is a practical framework for resilience planning which, in conjunction with the SLD's (Shared Learning Dialogue) framework, integrates resilience thinking into planning procedures in order to enable vulnerable groups to anticipate, respond to and recover from projected climate change impacts. URFalso provides resilience-related information to state and local mission partners, and supports their risk-based, resource decision making process (Tyler et al., 2010). The NIRA allows decision makers to investigate different resilience strategies by adopting different scenarios, as it investigates the reaction of networked infrastructure systems to disruptions.

The usefulness of resilience quantification results for managers and policy makers depends on the level and scale of the assessment and also the results' relation to policy, strategic planning and decision making, to point out where management and planning actions are needed. However, some models have limited their applicability to public awareness and education by their use of complicated methods (The ResilUS for instance); therefore their results are not easy to understand and are not simple enough to be used by a public audience.

2.5. Summary of Gaps in the Literature: Research Questions

In this chapter, the literature on resilience from urban hazards and disaster risks point of view is reviewed. It generated insight into the different definitions, attributes, components and current approaches in operationalising this concept. Critical analysis of these current approaches revealed a number of important gaps in operationalising the concept of resilience, particularly related to the scale, perspective and validity of the models.

This review revealed that most of the frameworks used for measuring disaster resilience are at a macro level (national, regional) or a micro level for specific networked infrastructure systems. In this context, there is a lack of comprehensive disaster resilience modelling at the local level. A resilience model at local scale could be more useful for urban planning and design, as communities at local spatial scale, such as at the neighbourhood level, are mainly the focus of hazard mitigation, disaster preparedness, disaster response and disaster recovery planning. This research seeks to bridge this gap by down-scaling the resilience model and developing a new neighbourhood disaster resilience index in an Australian context. This will need to specify the construct's conceptual domains and properties, identify the appropriate indicators for measuring resilience at neighbourhood level, reduce the dimension and aggregate the indicators to a composite indicator.

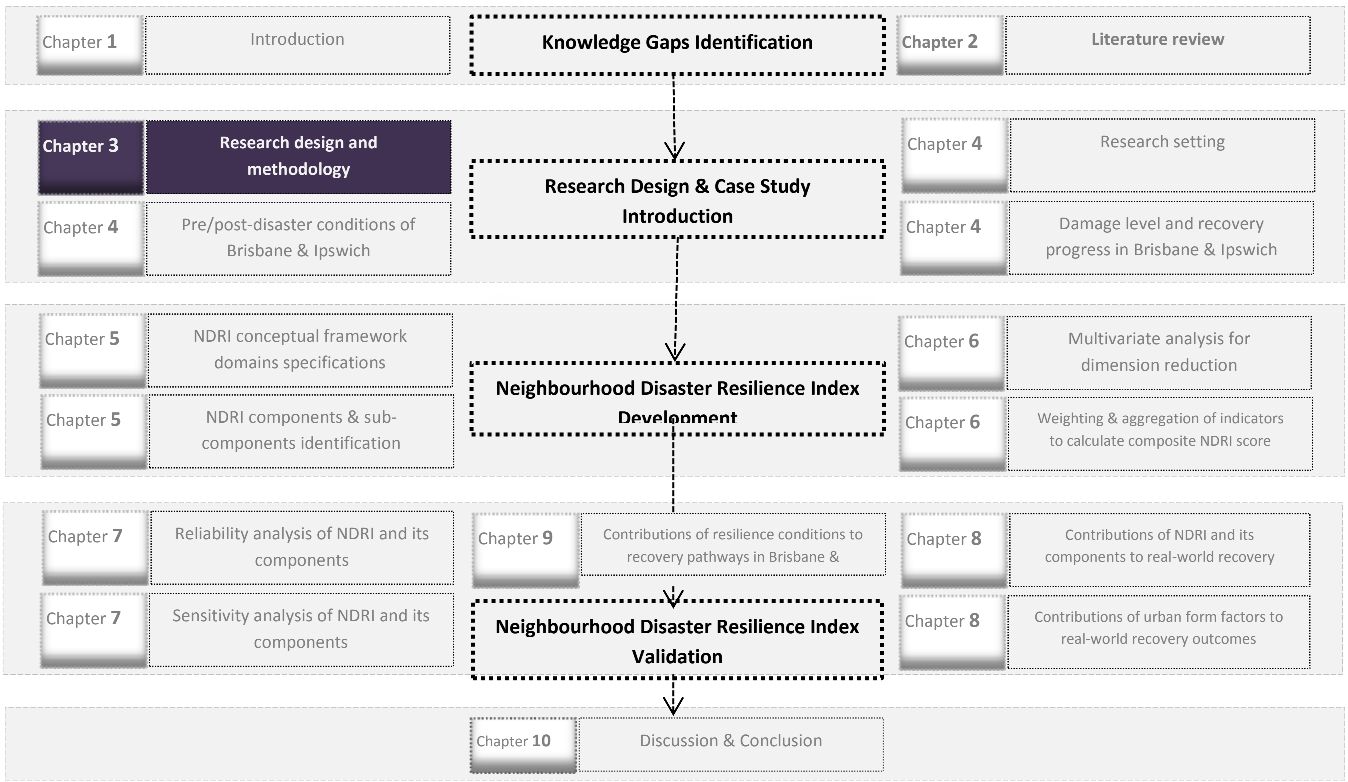
Moreover, the critical review showed that most of the current models have not been verified and validated as a construct by real world data. The validity assessment of the resilience measures are considered challenging in most cases due to lack of real-world data for disaster impact and recovery outcomes. The index validation needs different analysis for verification of the index's components and construct, along with analysis of its contributions to recovery outcomes and pathways using real-world data. For the first part, the reliability and sensitivity of the index needs to be examined. And for the second part of validation, the contribution of the proposed index to recovery outcomes needs to be investigated. Moreover, the contribution of new indicators, including urban form factors to recovery progress, needs to be investigated. Despite the indications in the literature on potential impacts of the urban form factors on disaster resilience of the place, there has been no investigation on the contribution of urban form variables to recovery progress. In addition, within the Australian context, there remains a lack of comparative recovery case studies available for investigation in order to understand the differences in the recovery progress and their link with pre/post disaster conditions at neighbourhood level.

To address these research gaps, this thesis seeks to answer two overarching questions and sub-questions outlined in Figure 2.11: 1) How can an urban disaster resilience model be developed at the neighbourhood level? 2) How can the neighbourhood disaster resilience model be validated by assessing its contributions to the recovery outcomes?

Gap in literature	Research question
The operationalization and measurement of disaster resilience at neighbourhood level has not been addressed comprehensively, taking into consideration the physical, social, economic and environment conditions. The current resilience models are mostly focused on large scales which may not meet local needs for urban designers and planners since each neighbourhood may have unique socio-economic and physical characteristics.	**How can an urban disaster resilience model be developed at the neighbourhood level?** • What is the nature of the resilience construct's conceptual domains and properties? • What are the key indicators of disaster resilience at neighbourhood level? • What set of variables provide the best parsimonious indicator set of disaster resilience at the neighbourhood level? • How these indicators can be merged into an overall resilience composite index?
Current resilience models are not validated comprehensively. For this purpose, the contribution of the proposed resilience model to real-world recovery outcomes needs to be examined. Several studies have emphasized the link between urban form and disaster resiliency. This hypothesis needs to be examined empirically to check whether they are appropriate for consideration in a resilience model. Moreover, a qualitative comparative study is required to understand differences in recovery processes and to understand the link between pre/post-disaster conditions of communities and broad recovery outcomes.	**How can the neighbourhood disaster resilience model be validated by assessing its contributions to the recovery outcomes?** • To what extent is the proposed model internally sound and robust? • To what extent is each indicator, sub-component and component of the NDRI contributing to recovery outcomes? • To what extent are the urban form variables contributing to recovery outcomes? • Which of these pre-disaster conditions and post-disaster factors and what combinations of them built pathways to the recovery of Brisbane's neighbourhoods?

Figure 2.11. Overview of the literature gaps and research questions

Chapter3
Research Design and Methodology



3. Research Design and Methodology

3.1. Overview

In the previous chapter the research gaps were identified. This thesis seeks to address two overarching questions: 1) How can an urban disaster resilience model be developed at the neighbourhood level? 2) How can the neighbourhood disaster resilience model be validated by assessing its contributions to the recovery outcomes?

This chapter details the methodology adopted to address the research questions. It also clarifies how the methodological approaches adopted align with the conceptual position and framework extracted from the literature review. This chapter begins with the overall research strategy and scientific paradigm employed in this research, which is followed by the methodological choices, data collection and data analysis methods. At the end of this chapter, the overall structure of the research design is presented.

3.2. Overall Research Strategy and Scientific Paradigm Justification

In order to find the appropriate research design and methods, it is necessary to understand the philosophical positioning of the research investigation. The literature suggests that there are varying conceptualisations which fit into a continuum of paradigms, rather than having rigid boundaries for each paradigm (Guba & Lincoln, 1994). Considering the aims and needs of this research, the critical realism (post-positivism) paradigm is considered to be the most appropriate paradigm in which to examine the issue of disaster resilience measurement at the neighbourhood level (Table 3.1).

The purpose of this investigation is to better understand and measure the complex phenomenon of disaster resilience in the context of urban systems at the neighbourhood level, as it is occurring in the real world involving the community and its economic and physical environment. Critical to this is the development of a construct to measure the phenomenon of disaster resilience, and the development of a descriptive assessment of damage and recovery in as proxies of disaster resilience, in order to compare and validate the results of construct scores. Accordingly, it can be said that this research is suited to critical realism, as it includes the subjectivity of the construct development as well as the objectivity of the real world recovery examination and validation. This is in line with ontological assumptions of critical realism.

Given that the complex nature of disaster resilience has not been fully comprehended, the emphasis here lies more on finding determinants emerging from reviewing the resilience literature from different perspectives. Resilience has rarely been investigated as a combination of non-positivist and positivist paradigms. Thus employing this research paradigm will help to enhance understanding and modelling of disaster resilience.

Table 3.1. Scientific paradigms used in this research and their philosophical assumptions

Scientific Paradigm	Ontology (reality)	Epistemology (relationship between researcher & reality)	Methodology (techniques can be used to discover the reality)
Phenomenological paradigm Post positivism (Realism)	Critical Realism Reality is 'real' but only imperfectly & probabilistically understandable (provisionally true)	Modified objectivist findings probably true; objectivity worth striving for	Mixed/ triangulation qualitative/quantitative Case studies/structural equation modelling

3.3. Methodological Choices

Such conditions as those discussed in the previous section support the suitability of the critical realism paradigm for this research, positioning it somewhere between the plain objectivity of positivism and the pure subjectivity of constructivism. Methodology choices are normally guided by the ontological and epistemological assumptions, therefore a limited range of methodological choices are relevant for this research, including case study, survey, structural equation modelling and other multivariate techniques as shown in the figure below.

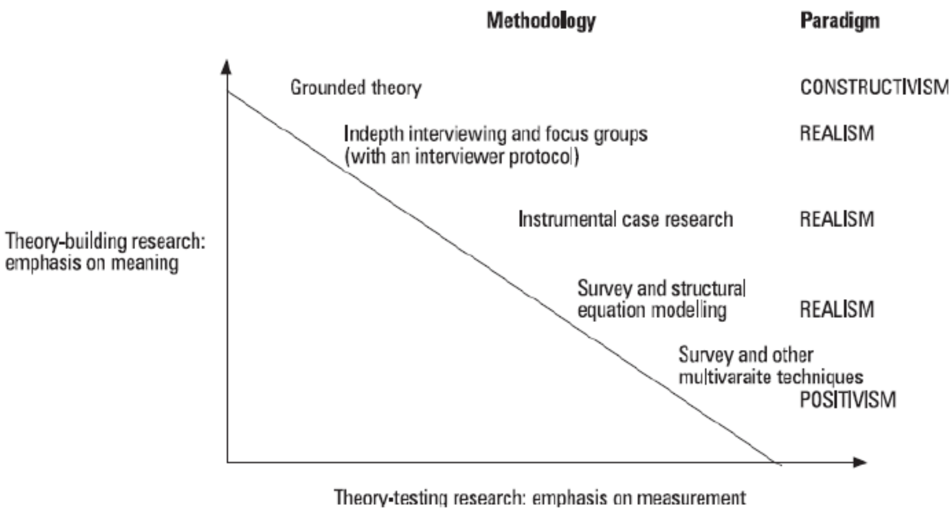


Figure 3.1. Methodologies by paradigm (Perry, 1998)

Each of these research strategies provides a way to collect and analyse empirical evidence and all have advantages and disadvantages. This research investigation includes five different parts as displayed in Figure 3.2. The research design and case study introduction part consists of the current chapter and Chapter 4, which introduces the case study area. A case study approach is chosen in order to collect the real-world data for validation. In this part, the recovery indicators will be identified, and damage and recovery processes of the study area will be examined using real world data and inductive reasoning. The third part, including Chapter 5 and Chapter 6, is the theory building module which follows deductive reasoning and attempts to develop a construct and measurement model for evaluating disaster resilience of urban systems at a neighbourhood level. Finally, to test the theory built from part three, the reliability and validity of the proposed model will be analysed using real world recovery outcomes. The use of both inductive and deductive reasoning offers synergistic benefits, since the use of just a deductive approach can limit the development of new theories that might be important in the field of study. On the other hand, focusing solely on inductive reasoning may prevent the use of already established theories (Perry, 1998). The methodological choices for parts two, three and four are described in detail in the following sections.

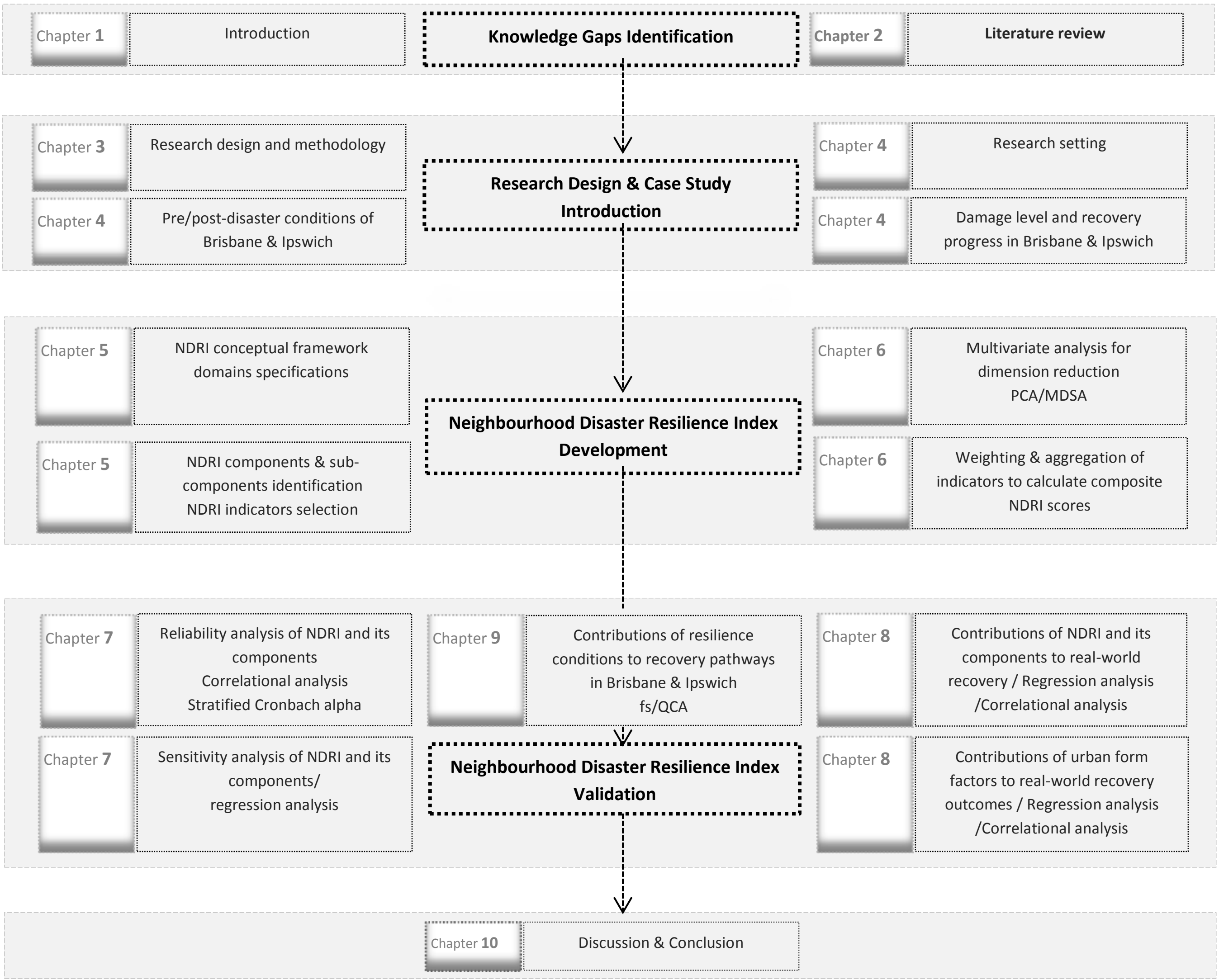


Figure 3.2. Research design and methodology

3.3.1. Case Study

In the validation section of this study, the design consists of a case study of embedded units (neighbourhoods). Single case studies are considered as basically restricted in their analytic approaches, since the replication logic cannot be employed to augment and draw strong conclusion. But the benefit of an embedded case design is that it allows for some comparisons among the embedded cases within a single case, and this is required in this study (Yin, 2013).

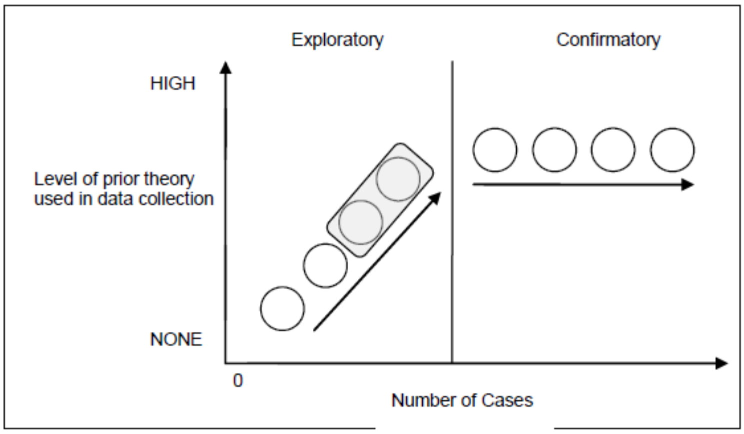


Figure 3.3. Number of case studies in exploratory and confirmatory research (Perry, 1998)

In terms of the objections to a single case study approach, Flyvberg (2006) has systematically addressed these misunderstandings about the case study approach, including beliefs such as 'case studies do not offer a suitable basis for generalisation and that the case study cannot contribute to scientific development'. He considers the debates and ultimately rejects this misunderstanding by suggesting that 'One can often generalise on the basis of a single case, and the case study may be central to scientific development via generalisation as supplement or alternative to other methods. But formal generalisation is overvalued as a source of scientific development, whereas "the force of example" is underestimated' (Flyvbjerg, 2006, p.228). This is especially useful within the context of this study where part of the methodological focus for validating and testing the proposed model will be on the 2011 Brisbane River flood event.

The case study chosen for this research is the flood-affected neighbourhoods of the Brisbane local government area (LGA) and the Ipswich LGA. The reason for this choice is that these are the most populated and the most flood sensitive areas in this region (Middelmann, 2007). The increasing hazard vulnerability in this area poses a challenge to planners and emergency managers on how to enhance the local communities' coping capacities and improve the disaster resilience within these areas. However, another important factor in choosing Brisbane and Ipswich is the availability of the data for testing and validating the model. As discussed earlier, the unit of analysis in this research is the neighbourhood which is assumed to be equivalent to suburbs in the Australian Census

Geographical Divisions. The neighbourhood level is chosen as it is intended to be fairly stable in population size and is homogeneous in terms of population characteristics, economic status and living conditions (Sampson et al., 2002).

The challenging issue is to determine whether any generalisations can be made from this case study. An understanding of the process requires distinguishing between two types of generalising: statistical generalisation and analytic generalisations (Yin, 2013). The fact is that a single case cannot generalise in the usual manner, nor it is intended to. A common incorrect assumption is that statistical generalisation, from samples to universes, is the only way of generalising findings from social science research. In contrast, analytic generalisations depend on using a study's theoretical framework to establish a logic that might be applicable to other situations. Generalisations from cases are not statistical, they are analytical. They are based on reasoning. There are three principles of reasoning: deductive, inductive and adductive. Generalisations can be made from a case using one or a combination of these principles (Johansson, 2003). The objective for generalising the findings of the case study in this research is based on deductive reasoning to show how this study's findings can inform the relationships among a particular set of concepts, theoretical construct, or sequence of events regarding community resilience.

Single cases are commonly used in case studies, and two variations of single case studies have been described by Yin (2013) as being holistic and embedded. Overall, he argues that the single case design is highly justifiable under these certain conditions - where the case represents: (a) a critical test of existing theory; (b) a rare unique circumstance; (c) a representative or typical case; or where the case serves a (d) revelatory or (e) longitudinal purpose. In the context of this research, the first condition is applicable.

It is important to note that this model is a theory-driven model, not a data-based model. Thus, in the initial stages of modelling, the case study is not considered for variable selection. However, in the end, a case study is considered for calibration and validation of the model. This is based on Yin's justification for a single case study where we are testing the existing theory. Within this single case, a range of units within one place have been incorporated, so that an embedded design is developed. This adds more opportunities for extensive analysis and to enhance the insights into the single case.

In summary, to the extent that this study concerns itself with generalising, the case study tends to make limited generalisations to other situations on the basis of analytic claims by deductive principle reasoning. By comparing the expected findings which are deduced from a theory and a case with the empirical findings, it will be possible to verify or falsify the theory.

3.3.2. Neighbourhoods Disaster Resilience Index (NDRI) Development

The methods selected for this part of the research are based on the composite indicators construction method. This method provides a 'holistic' assessment of disaster resilience which will be validated later with real-world data from the 2011 flood in Brisbane and Ipswich to inform and improve the model. The development of composite indicators is not new and a vast body of literature on composite indexes exists that outlines methodological approaches for index construction. Most of the literature highlights the need for a stepwise process of index construction (Freudenberg, 2003; Nardo et al., 2005; Saltelli et al., 2005).

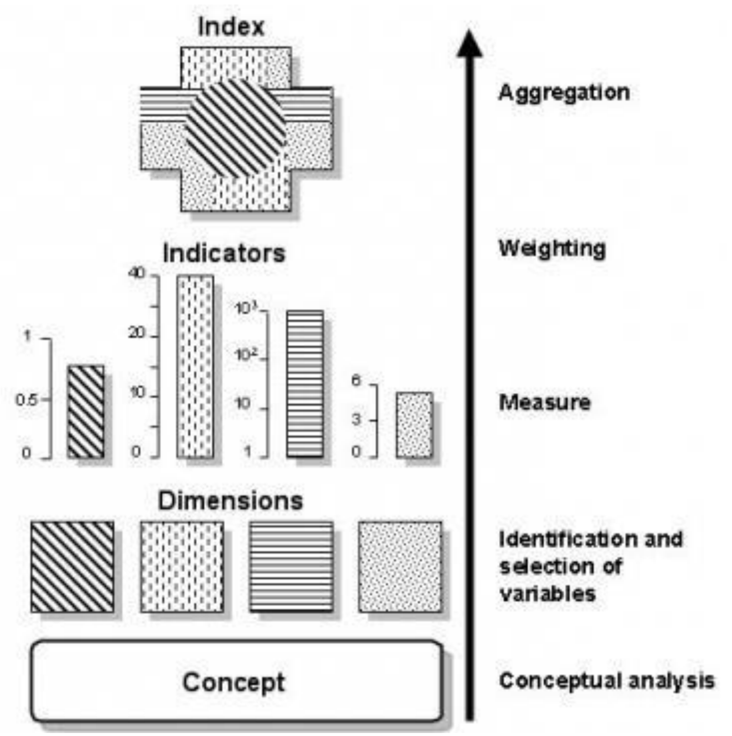


Figure 3.4 Composite indicator construction steps (Wong, 2006)

The methodological steps taken for the development of the Neighbourhood Disaster Resilience Index are described below.

Developing the Theoretical Framework of the Construct and Specifying the Intended Model

Chapter 5 covers the first step in the development of the NDRI, the conceptual framework and the model specifications (Figure3.4). Meredith (1993) lists different types of conceptual research under conceptual models, conceptual frameworks and theories (Table3.2). The aim of this section is to develop a conceptual model consisting of a set of logically related propositions which state the relationships among the variables. Conceptualization was processed through a review of previous theoretical and empirical research on the focal construct, disaster resilience (MacKenzie et al., 2011). The intended model was then specified and the theoretical boundaries for this research were thoroughly set in Chapter 5.

Table 3.2. Types of conceptual methods (Meredith, 1993)

Conceptual models
1. Conceptual description
2. Taxonomies and typologies
3. Philosophical conceptualization
Conceptual frameworks
4. Conceptual induction
5. Conceptual deduction
6. Conceptual systems
Theories
7. Meta-frameworks

The use of existing conceptual research methods and model specifications in the literature offered a significant opportunity for this study to build valid theoretical assumptions for the intended Neighbourhood Disaster Resilience Index. Thus building on a review of the structure and dynamic of earlier models in Chapter 2 (Table 2.3), and a heavy dependence on real world descriptions, led to an improved synthesize of previous models by adding some mediators and moderators, explained in detail in Chapter 5.

Variable Selection: Thematic Analysis and Cross Classification

The second phase of the index development consisted of the identification and development of relevant variables, which is covered in Chapter 5. The strengths and weaknesses of the composite indicator are mostly derived from its variables. Two basic methods of selecting indicators can be identified in the literature (Wong, 2006).

1. Bottom-up: This starts with a long list of possible indicators and then narrows them down as the research progresses, either on the basis of meta-criteria or on the basis of practical experience.

2. Top-down: This method starts with defining the principles, objectives, concepts or standards which one wants to measure, breaking them down into different dimensions and finally developing indicators for each of these dimensions.

The most suitable way to design indicators depends on the type of indicators we are looking for. The bottom-up method can be useful for individual indicators, because it may yield more creative indicators. But in this study, the top-down method of composing indicators seemed more appropriate, as a comprehensive model was intended and an aggregated result was more important. On the other hand, utilizing this method makes the inter-linkages between indicators and their proportionate weights clear, as well as clarifying their relationship to the larger principles, objectives and concepts that we want to measure (Churchill Jr, 1979).

The variables of resilience and recovery were identified through thematic analysis of the literature and a critical review of previous models. The commonly recurring themes and indicators for measuring disaster resilience were cross-classified in a matrix by resilience attributes and resilience dimensions (Table 5.1). This cross-classification assured that all indicators associated with resilience attributes in each component were included in the construct. Finally, choices among indicators were guided by a set of criteria. First, it was essential that variables be justified based on the extant literature on the variable's relevance to resilience. The second criterion was that variables must be of consistent quality data from data sources (e.g. insurance data was not publicly available) and the third criterion was to check whether variables were available at our scale of interest (e.g. GDP is not meaningful at neighbourhood level).

Dimension Reduction: Multivariate Analysis for Refinement of Selected Variables

The underlying nature of the dataset was analysed to avoid the 'indicator rich but information poor' situation in developing composite indicators. In fact, multivariate analysis was needed to check whether the nested structure of the disaster resilience composite indicator was well-defined and well-balanced, and also to identify the group of indicators that were statistically similar. These analyses also supported the refinement of the selected variables by dropping the metrics which cross-load on more than one factor, and also validate the developed index by demonstrating the loading of each indicator on each component. It also facilitated the subsequent methodological choices for weighting and aggregation.

Figure 3.5. Possible structure of commonalities of variables within a model

The commonalities of variables were assessed to investigate the dimensionalities within each component. Different possibilities of commonalities between variables are displayed in Figure 3.4. The figure on the right hand side shows that the overall structure of the measured commonalities is totally heterogeneous, while the figure on the left shows that the measure is not totally uni-dimensional nor completely heterogeneous. Therefore, considering the multi-dimensionality, interpretability and importance of variables, the number of variables will be reduced, revealing the dimensions of the original dataset prior to modelling. Factor analysis is a well-known statistical method used to reveal how different variables of the developed index are associated with each other. By transforming the correlated metrics to a new set of uncorrelated factors using a covariance matrix, also revealed is how the variables are changing in relation to each other. In fact the new factors are the linear combinations of the original metrics sorted in descending order based on the variance they explain in the original data set. The main weakness of the factor analysis stems from the fact that it needs to meet special assumptions such as distribution, linearity and multivariate normality (Hair et al., 2006). This makes this method somewhat inadequate in explaining the given relationships and drawing inferences on the data.

Initial examination of the variables showed some violations from these assumptions. Thus, in order to get a satisfactory, reliable result, principle component analysis and multidimensional scaling were utilised as non-parametric methods which do not need these assumptions, to analyse the data structure. This helped to reduce the dimensionality within the dataset and to derive a parsimonious variable set which is estimated to be sufficient and appropriate to describe the resilience phenomenon and guide subsequent methodological choices for weighting and aggregation (Nardo et al., 2005).

Calculation of Composite Index (NDRI) and Its Components

Scale adjustment and normalisation

Normalization for the purpose of cross comparison is required prior to any data aggregation, as the indicators in a dataset often have different measurement units. Thus, in order to avoid adding dissimilar factors, and to be able to combine and compare indicators, we need to make them unit-less. A number of normalization methods exist that can be used in this regard (Freudenberg, 2003; Jacobs et al., 2004): ranking, Z-scores, min-max, etc. For the purpose of this research a min-max rescaling scheme was used to create a set of indicators on the same measurement scale. The reason for avoiding the other methods is that their scaling factor is based on a range rather than a standard, which could result in large impact of the outliers on the index and bias the results (Freudenberg, 2003).

Weighting

In order to combine the selected indicators to develop a composite indicator in a meaningful way, it is necessary to decide which weighting model should be used and how the components and sub-components should be aggregated. According to Nardo et al. (2005) there are a number of weighting techniques, some derived from statistical models (parametric) and some derived from participatory methods (non-parametric). Statistical models for weighting normally include factor analysis, unobserved components models (UCM), principle component analysis (PCA). Participatory methods normally include the budget allocation process (BAP), the analytic hierarchy process (AHP) and conjoint analysis (CA). As well as deciding about these methods, it is also necessary to consider the possibility of using other methods for multi modelling. Moreover, it should be decided whether or not compensability among indicators and correlation between indicators should be accounted for.

In this research Equal Weighting (EW) and PCA are used as weighting methods and then their effect on the final neighbourhood resilience scores was tested. However, the impact of weighting cannot be over emphasized, as it should be remembered that no matter which method is used, these weights are usually value judgements and all assumptions and implications of the used weighting system should be clear and tested for robustness and transparency.

Statistical models for weighting account for the highest variation in the data set, using the smallest possible number of factors that reflect the underlying statistical dimensions of the dataset. This sort of weighting does not consider the theoretical importance of each variable, rather it interferes just for correction of overlapping information of the correlated variables. In this research principle component analysis has been used as a parametric solution for weighting, assuming that there is some structure behind the variation of the included indicators. Hence the weights for these indicators are determined objectively by the covariation between them on each dimension of the structure. The use of factor score regression weights obtained from the PCA model minimizes measurement errors in the indicators contributing to each composite scale, thus increasing the reliability and validity of the computed composite scores. Participatory methods were not considered in this study as these methods needed a wide range of experts in the case study area.

An equal weighted component score is simply a summation of the scores on all the variables that loaded strongly on a particular component. The major difference between equal weighted component scores and PCA component scores is that the original variables are not multiplied by optimal weights. As such, this will often result in component scores that are not orthogonal. It should be noted that there are different number of variables in each dimension and this can ruin the balance of the final Composite Indicator (CI) since the dimensions with more indicators will have implicitly higher weights in calculating the composite index (Nardo et al., 2005). For this reason, in creating sub-indices the averaging method was used to reduce the influence of different numbers of indicators in each subcomponent. In other words, the subcomponent scores for the social, economic and physical dimensions were calculated by the summation of equally weighted average subcomponent scores. Since there are three subcomponents of resilience in this study, the summed score of the composite index ranges between zero and three (zero being the least and three being the most resilient).

Equal weighting (EW) has a compensatory logic, and using it in a composite index would imply that one is willing to accept, for example, 10% more in unemployment in exchange for a 10% increase in income. Considering the complexity of the resilience concept itself and the number of indicators, EW has been used by most of the previous models for aggregation.

Aggregation

Nardo (2005) suggests three general aggregation methods in developing composite indicators including additive, geometric and multi-criteria aggregation. In fact, the selected indicators could be summed up, multiplied or aggregated using non-linear techniques. Each of these techniques has different assumptions and each has particular consequences.

Compensability is an important element of aggregation methods. In fact, aggregation methods with compensability allow a neighbourhood that has a good score on many indicators to have a better overall score compared to a neighbourhood that does better on a few indicators. In this regard, additive aggregation implies a full compensability, while multi-criteria is a non-compensability method and the geometric aggregation is the intermediate solution. An example is if we have two neighbourhoods with one having social, economic and physical resilience scores of 32, 2, 2 and the other having scores of 12, 12, 12. This would have an equal composite score if the additive aggregation method was used, while perceptibly these two suburbs would have very different conditions which would not be revealed in the composite score by the use of this method.

Table 3.3 shows the relationships between aggregation and weighting methods in developing composite indicators. These combinations would guarantee that we would not lose information in the mathematical procedures.

Table 3.3. Compatible weighting and aggregation methods (Nardo et al., 2005)

Weighting methods	**Aggregation methods**		
	Linear	**Geometric**	**Multi-criteria**
Equal weighting	Yes	Yes	Yes
Principle component	Yes	Yes	Yes
Benefit of doubt	Yes	No	No
Unobserved component models	Yes	No	No
Budget allocation	Yes	Yes	Yes
Analytic hierarchy process	Yes	Yes	No
Conjoint analysis	Yes	Yes	No

Multi-criteria aggregation (MCA), on the other hand does not recompense outliers as it keeps only the ordinal information, and also it does not provide the results in terms of an index, rather only giving the ranking of suburbs. Thus a better rank for a given suburb at two different times may not indicate an overall improvement in that suburb, but deterioration in other suburbs in the set.

Accordingly in a benchmarking exercise, if the aggregation method is geometric, a neighbourhood will be more inclined to enhance the sectors with the lowest score in order to have the highest chance of improving its position in the ranking. On the other hand, when the aggregation method is linear, the neighbourhood has an interest in specialising in its most effective dimensions.

After obtaining the scores of each component, these scores need to be aggregated to allow cross comparisons among neighbourhoods within the study area. There are different aggregation methods: linear, geometric and multi-criteria. Where all individual indicators have the same measurement unit, most of the previous models have utilized the linear aggregation method. Geometric aggregation, on the other hand, is a better fit if we want some degree of non-compensability between individual indicators or dimensions. In the context of this research it is necessary to ensure that weights will remain a measure of importance and different dimensions of indices are equally legitimate and important, therefore methods that do not allow compensability seem more suitable for this study.

Considering the theoretical framework specifications and also the earlier discussion on not allowing compensability among indicators, linear summation is considered to be the most appropriate procedure for aggregation in this research.

3.3.3. Neighbourhood Disaster Resilience Index Validation - Confirmatory Research

In this step, the credibility of the proposed index was examined through different empirical testings.

Reliability and Validity Assessment of the NDRI

The reliability assessment calculates the extent to which the indicators provide consistent results over repeated measurements (Babbie, 2013; Lo, 2013). In general, there are three main concerns in a reliability analysis: equivalence, stability over time and internal consistency (Figure 3.6).

However, temporal stability is not the case in this research as theoretically the proposed measure is not expected to remain stable over time. Across situations, resilience measure is a dynamic issue, varying by dynamic variables over long period of time. On the other hand, retesting over short period of time would be meaningless, as most of the data sources would be the same as previous secondary sources. In terms of equivalence reliability, the Social Vulnerability Index (SOVI) has been used to test the equivalence reliability. The correlation between the alternative form and the NDRI shows whether or not the measurement error in the present scale is considerable.

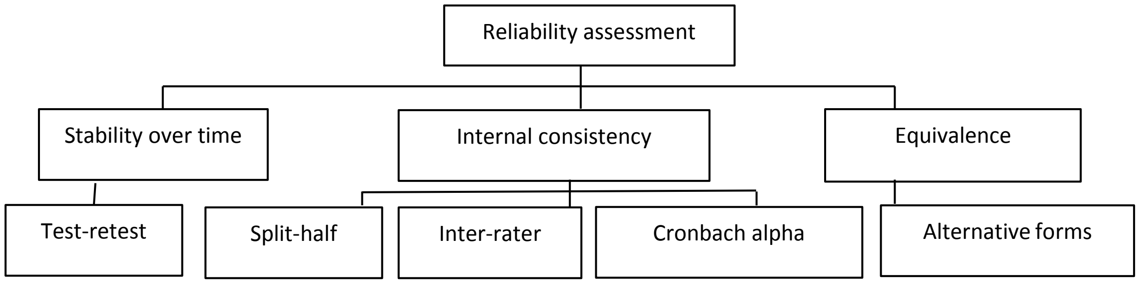


Figure 3.6. Key concepts and methods of reliability assessment
(Carmines & Zeller, 1979)

In terms of internal consistency, it should be noted that as mentioned in the 'model specification' section, the intended construct in this thesis is a third order formative construct. The formative indicators are not interchangeable as in a reflective component, and therefore in most cases, internal consistency is not a necessary assumption. Bagozzi (1994, p 40) warns that "reliability in the internal consistency sense and construct validity in terms of convergent and discriminant validity are not meaningful when indexes are formed as a linear sum of measurements". However, internal consistency assessments could facilitate the refinement and purification of indicators. Indicators that show very low corrected item-correlation will be removed from the scale (corrected item-total correlation is the correlation of an item with the total score of all other items in a scale). Considering the theoretical context of this study, the split-half method was a desirable method for consistency assessment if we had enough data, but as the number of items in our dataset is limited, this cannot be used as a proper, reliable method of assessment.

Moreover, three aspects of the reliability of the multidimensional measures are distinguished in the literature: the share of the variance in each measurement item explained by the latent variable (individual item reliability, which has been assessed using inter-item correlation analysis), the amount of scale score variance that is accounted for by all underlying factors (composite reliability that has been evaluated using stratified Cronbach alpha) and the degree to which the scale score reflects one particular factor which represents construct reliability (Brunner & SÜβ, 2005; Coltman et al., 2008).

Validation of NDRI: The Contribution of Disaster Resilience Factors to Recovery Outcomes

As previously mentioned, resilience and recovery are multidimensional concepts and therefore, finding the reliable quality data to validate the model comprehensively is difficult (Nardo, 2008; Vincent, 2004). The indicators of the abstract concept are valid to the extent to which it measures what it was supposed to measure. Validity concerns the crucial relationship between concept and indicators selected for measuring the concept. However, the literature on indices and composite indicators emphasizes that validation of indices are a complex process. The important types of validity are introduced in Figure 3.7. These types of validity require different approaches of validity assessment.

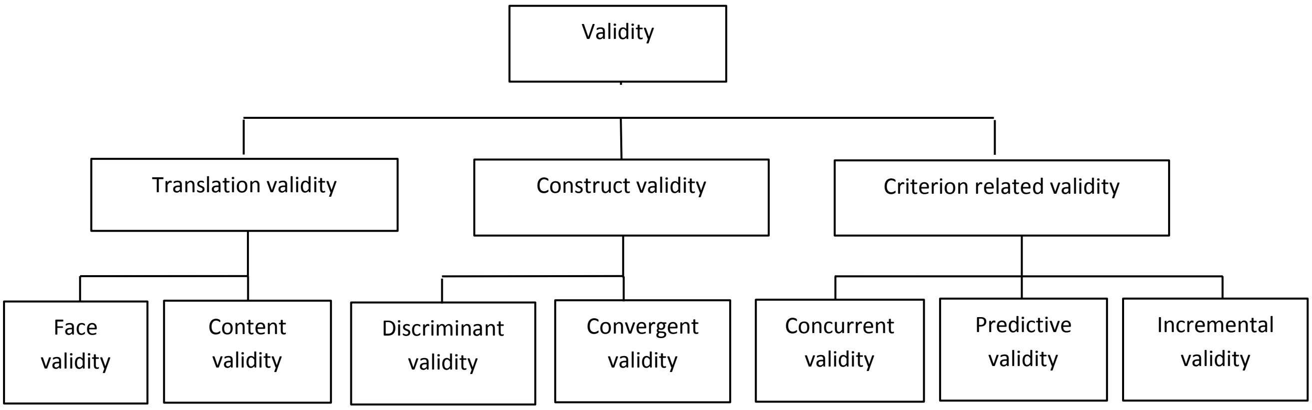


Figure 3.7. Validation assessment categories
(Carmines & Zeller, 1979)

Content validity assesses the extent to which the scale reflects a specified domain of content (Lo, 2013), which means to obtain a content valid scale. It is required to specify the full domain of the content that is relevant to this particular measurement situation. In this research, this has been checked through the selection process by using a cross classification method within the proposed framework.

Discriminant validity is not the case in this research as NDRI is a formative index. However, in assessing the convergent validity, the correlation of NDRI with measures of the same or similar construct (SOVI—SEIFA) are tested using Spearman correlationr.

The predictive validity of the index was assessed using a set of regression models including the zero-truncated poisson (ZTP) regression model, the ordinary least square (OLS) regression model, and non-linear logistic regression. Moreover, R square change analysis is used to indicate the extent to which the subcomponents of resilience predict the recovery outcome in time, and also to render the overall predictive power of the sub-components of resilience with the irrelevant parameters removed.

The ability of each item to add incrementally to the prediction of the outcome measure is called incremental validity. Thus in this research the goodness-of-fit of the current model is compared with a specified “null” model to determine the degree of improvement over the null model.

In Chapter 8, the influence of urban form indicators on the recovery of the Brisbane neighbourhoods' recovery after the 2011 flood is assessed. To test the hypotheses regarding the impact of urban form on housing recovery outcomes, a series of multiple regression and correlational analysis was conducted, analysing the relationships between urban form variables as the independent variable, and disaster recovery outcome as the dependent variable. Although longitudinal data of reconstruction progress after the flood is being used to detect the suburbs' recovery status, the research design is cross-sectional and does not offer the ability to document causality.

Qualitative Comparative Analysis of Brisbane Neighbourhoods after the 2011 Flood

A fuzzy-set qualitative comparative analysis (QCA) has been used in Chapter 9, which provides a middle ground between a case study and statistical analysis through set theory and fuzzy logic. The first step in QCA involves identifying a particular outcome of interest, besides the conditions that are theorized to have an impact on outcomes. In this research, the recovery outcomes are identified along with the pre-disaster and post-disaster conditions that theoretically affect recovery outcomes. Then all the possible complex combination of conditions that could result in targeted outcome are analysed. By these calculations, the causal conditions that were either necessary or sufficient for housing recovery are also assessed. Later, the consistency (the degree to which neighbourhoods with a given set of causal conditions show the same recovery level) and coverage (the degree to which a given pathway explains the neighbourhoods) are measured (Ragin, 2008).

A diverse set of neighbourhoods, including 26 flood-affected neighbourhoods, was selected, as the truth table should consist of a variety of values for both conditions and outcomes in order to determine variation and similarities amongst the neighbourhoods. Both qualitative and quantitative data were collected across the 26 selected neighbourhoods. In fuzzy-set QCA, each condition and outcome was assigned a value from the range of 0 (completely out of the set) to 1 (completely in the set). This method is selected as we wish to comparatively analyse recovery in Brisbane neighbourhoods affected by the 2011 flood, and it includes a wide range of data values collected from qualitative and quantitative sources.

3.4. Research Limitations

The objective of this research is to develop a neighbourhood level disaster resilience index for Australia that could be validated with real world data. This research has several limitations since this is one of the few resilience measurement models that uses an empirical approach for development and validation.

In this study, the NDRI is developed from the synthesis of disaster resilience components using different weighting (principle component analysis and equal weighting) and aggregation (linear, geometric) methods. However, these methods depend on assumptions such as equal importance of all variables in an equal weighting approach and full compensability in a linear aggregation method. This may pose some limitations in creating a quality composite indicator. This limitation is addressed to some extent by calculating different alternatives and then using sensitivity analysis to gauge the robustness of the effects of weighting and aggregation decisions. This limitation can be better resolved by calculating additional alternatives undertaking AHP (an analytic hierarchy process) for weighting and a multi-criteria method for aggregation.

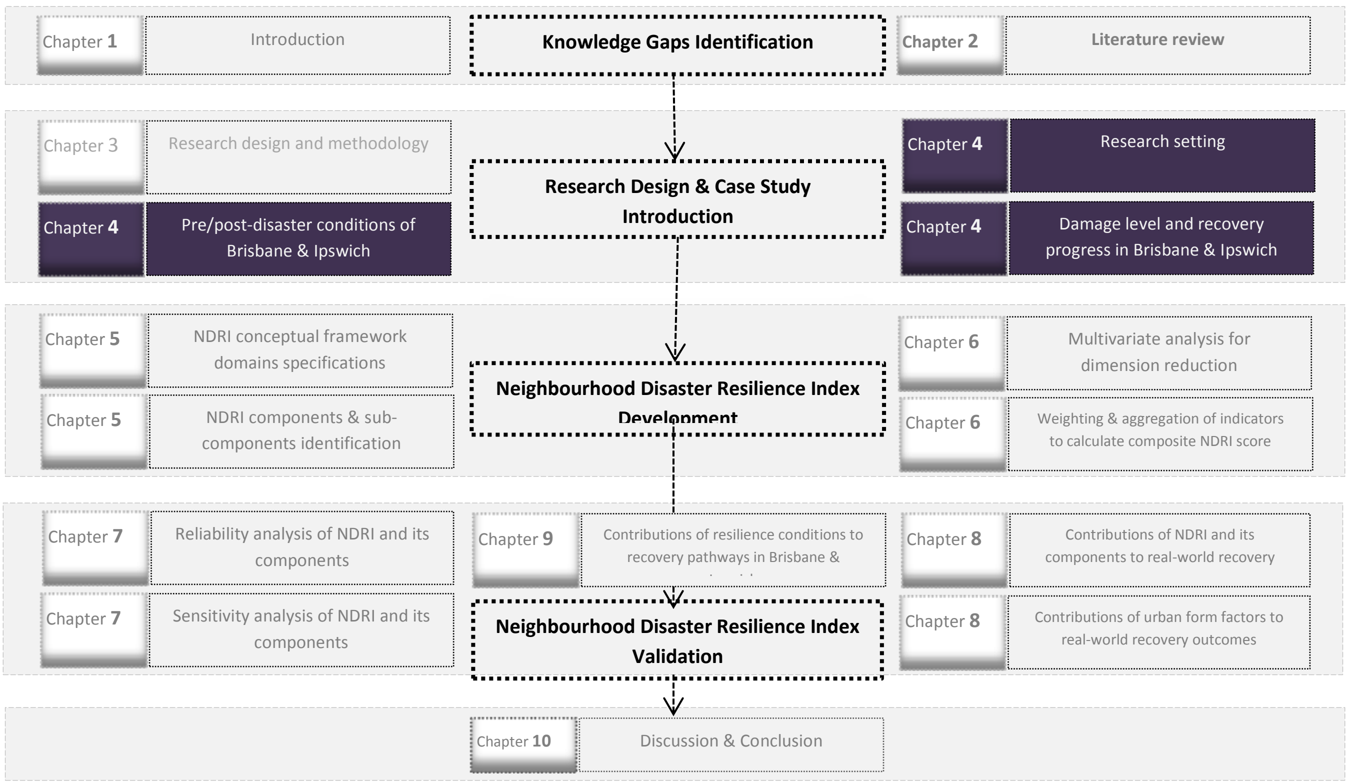
Another limitation of this study is that the results and findings of this study are constrained by the context of the Australian governance and databases. For example, insurance data are important for assessing reconstruction processes, but were not available at the neighbourhood level. Moreover, some of the findings in this research may not be applicable to other contexts. For instance, in other contexts, the urban form factors might have totally different impacts on the resilience of the community. Also, the findings are limited to a context where the threat is riverine flood. It would have been useful to study multiple disasters and contexts and see their interconnections; however, it was not feasible due to limitations of time and resources for a PhD project. One of the important issues to be considered in collecting data for composite indicators is the time of data collection for each indicator. Collecting data for NDRI as a snapshot composite indicator needs to meet this timing issue. For example, Census data used in this study for NDRI calculation is collected in August 2011 which is about seven months after the case-study flood in this research as previous census round of census data was too old to assess the dynamics of neighbourhoods. However, the impact of this timing issue is limited to a few indicators such as volunteer work participation which could be inflated in the event of flood emergency. The usage of these data are justified by the fact that the core concept that is meant to be measured here is community cohesion and it does not make a difference to use Census data before or after the flood as long as we can assure that the community living in the neighbourhood has a high level of cohesion to participate in volunteer works.

3.5. Summary

This chapter began by reviewing the overall research strategy and discussing the methodological choices, presenting the justifications for the use of the proposed methods. The table below shows the methods used to answer each research question and their corresponding chapters.

Overarching RQs	Research questions	Research methods	Chapter
How to develop an urban disaster resilience model at the neighbourhood level?	What is the nature of the resilience construct's conceptual domains and properties?	Content analysis	**5**
	What are the key indicators of disaster resilience at neighbourhood level?	Content analysis	**5**
	What set of variables provides the best parsimonious indicator set of disaster resilience at the neighbourhood level?	Multivariate analysis PCA/MDSA	**6**
	How can these indicators be merged into an overall resilience composite index?	Equal/PCA based weighting Linear/geometric aggregation	**6**
How to validate the proposed neighbourhood disaster resilience model by assessing its contributions to the recovery outcomes?	To what extent is the proposed model internally sound and robust?	Stratified Cronbach alpha correlation/regression analysis	**7**
	To what extent is each indicator, sub-component and component of the NDRI contributing to recovery outcomes?	Regression analysis	**8**
	To what extent are the urban form variables contributing to recovery outcomes?	Correlation/regression analysis	**8**
	Which pre-disaster conditions and post-disaster factors and what combinations of them built pathways to recovery?	Qualitative comparative analysis/QCA	**9**

Chapter 4
Research Setting: Case Study Introduction



4. Case Study Introduction

4.1. Overview

In this chapter, the case study used for validation is introduced in three sections. First, the research setting, including the area and the disaster which affected that area, are introduced. Second, the data sources used to collect the required data are presented, and finally the conditions and recovery outcomes in the case study area are discussed.

4.2. Research Setting

Australia is no stranger to large scale and devastating natural disasters, including catastrophic bushfires, far reaching floods, and damaging storms. In fact, natural hazards are a feature of the Australian climate and landscape, and this threat will continue as climate change is making weather patterns less predictable and more extreme (Council of Australian Governments, 2011). On the other hand, the growing intensity of settlements and concentration of material assets are mostly located in coastal areas that are prone to these hazards, thus ensuing greatly amplified vulnerability for human settlements in Australia (Middelmann, 2007).

Figure 4.1. Map of flood hazard areas in Australia (Geoscience Australia)

The Study Area

The case study chosen for this research is the flood affected neighbourhoods of the Brisbane local government area and the Ipswich local government area. The reason for this choice is that these are the most populated and most flood sensitive areas in this region (Middelmann, 2007). The increasing vulnerability to hazard in this area poses a challenge to planners and emergency managers as to how to enhance local community coping capacities in order to improve the disaster resilience within the area. However, another important factor in choosing Brisbane and Ipswich is the availability of the data to test and validate the model. The Brisbane local government area and the Ipswich local government area have jurisdiction over these neighbourhoods. Brisbane's LGA is the largest local government in Australia with a population of 1,041,839 (ABS, 2011) and a land area of 1,367 square kilometres, which delivers core local government services including roads, infrastructure and environment protection as well as neighbourhood planning (Alizadeh, 2015).

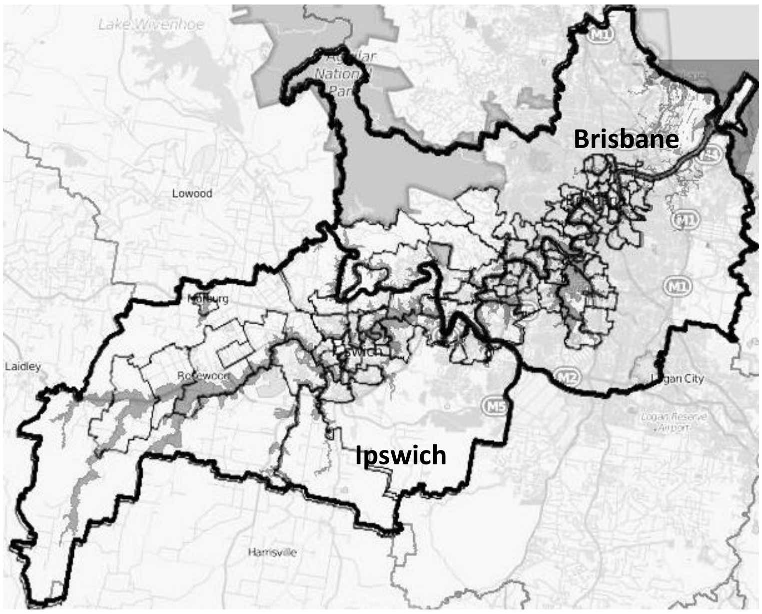


Figure 4.2. Brisbane and Ipswich flood affected areas in December 2010 and January 2011

(Department of Natural Resources and Mines, Australia)

According to the intersection of the 2011 flood boundary map and Brisbane and Ipswich neighbourhoods map, 175 from 253 neighbourhoods are affected by flood in January 2011. The percentage of flood affected areas in these was from .01% to 90.98. On average, 15.28% of these neighbourhoods are flooded with a standard deviation of 17%. Out of these 175 neighbourhoods, 102 neighbourhoods of Brisbane and Ipswich are included in the DARMsys survey. The percentage of the flooded area in these neighbourhoods ranges from .42% to 90.98% with an average of 23.65%. However, 26 of these neighbourhoods did not endure any property damages from flood (Brisbane City, Herston, Lanefield, Muirlea, Acaciaridge, Amberley, Booval, Bowen Hills, Brookfield, Chapelhill, Coopersplains, Fortitude Valley, Hamilton, Morningside, Pine Mountain, Pullenvale, Purga, Raceview, Rosewood, Salisbury, Seventeenmile Rocks, South Brisbane, Wacol, Willawong, Wilston, Yamanto). Thus, the damage and reconstruction data for these 76 neighbourhoods of Brisbane and Ipswich is available and can be investigated for their recovery process. The percentage of flooded area in these 76 neighbourhoods ranges from 1.8% to 91% with an average of 27.37%. Because of the data availability, different number of neighbourhoods is used for each component to conduct multivariate analyses in dimension reduction section.

The Queensland Floods 2010/2011

The major 2010/2011 flood in Queensland is one of the most recent disasters, and it affected about three quarters of Queensland, throughout most of the Brisbane River catchment including Brisbane, the state capital of Queensland. Brisbane is not unfamiliar with flooding and had experienced severe floods back in 1893 and 1974. In the 2010/2011 floods, devastation covered low lying areas of Brisbane, Ipswich, the Lockyer Valley and the Somerset regions, affecting many lives and thousands of properties. In the days leading up to the flood event, the estimated average rainfall over the Brisbane catchment area was 320mm. Wivenhoe Dam, built after the January 1974 floods, mitigated the flow from the Brisbane and Stanley rivers, however the most vigorous surges Brisbane experienced during the time were from flows emerging from the Bremer and Lockyer rivers. The heaviest rainfalls were recorded on the 11th January, 2011 in the Western fringe of the Brisbane river catchment, causing most affected residents to evacuate as their homes had begun to be inundated. Due to the diverse topography, the water levels varied across the river basin, with some areas and neighbourhoods experiencing greater flooding than recorded during the 1974 event, while others were not as badly affected.

The 2011 flood caused loss of life and an estimated 18,000 properties were inundated in the Brisbane River valley. The Insurance Council of Australia claimed that about 56,200 insurance claims were received that led to payouts estimated at $2.55 billion. Around 3,570 business premises were flooded. The Australian Emergency Management Australia Disasters Database estimated that 28,000 homes needed to be rebuilt, while vast numbers of dwellings required extensive repairs (van den Honert & McAneney, 2011).

Figure 4.3. Brisbane flood 2010/2011 (Australian Federal Police (AFP))

As discussed in Chapter 3, the unit of analysis in this research is the neighbourhood which is assumed to be equivalent to suburbs in the Australian Census Geographical Divisions. The neighbourhood level is chosen as it is intended to be fairly stable in population size and is homogeneous in terms of population characteristics, economic status and living conditions (Sampson et al., 2002). Moreover, most of the previous studies (Balsells et al., 2011; Carpenter, 2014; Mayunga, 2009; Pais & Elliott, 2008) on disaster recovery measurement and monitoring, call for more studies at sub-county or neighbourhood level, which would yield more geographically fine grained insights into the recovery process.

The Flood Recovery in Study Area

Following the 2010/2011 flood, the reconstruction authority of Queensland and other academic and governmental researchers carried out many different surveys, field studies, questionnaires and interviews to assess different aspects of the flood and post-disaster recovery (Bird et al., 2013b; Holmes, 2012; King et al., 2014; Mason et al., 2012; Wickes et al., 2015). This created a unique opportunity for this study to gain access to a variety of data sources which cover what is needed to assess the multi-dimensional aspects of resilience and recovery.

Eves et al. (2011) conducted a detailed analysis of the residential property market in Brisbane after the 2011 flood. They found that vacancy rate/rental listings significantly declined after the flood due to the high demand by flood victims and also due to the traditional demand at that time of the year caused by the influx of university students. Flood-affected victims preferred to stay in the same neighbourhood, however, some victims did leave their neighbourhoods to move into units in high value areas. There is no significant correlation between house ownership and recovery process. However, Bird et al. (2013) report the different decisions faced by the owner occupants of single-family houses compared to investors in rental properties. Furthermore, they indicate that recovery policies focus more on assisting owner occupants, with very few programs addressing housing owned as investments. For example, an interviewee in Bird et al.'s (2013) study reports that his tenants had moved out, he did not qualify for any relief funds, and so was trying to rebuild the property himself.

While there was a 40% fall in house and unit listings immediately after the flood, home sales became abnormally active in non-affected neighbourhoods (Eves, 2011). However, as was expected, after this major fall, sales listings in the affected neighbourhoods showed a greater rate (60% rise) compared to the non-affected neighbourhoods (20% rise). Eves et al. (2014) showed that the housing market in Brisbane after the flood was determined to a great extent by the location of the residential property. This increase in sales listings was greater in lower value neighbourhoods. This could be due to lower insurance cover in lower social-economic areas or the owners taking the opportunity to sell and move to flood safe areas. The findings from Eves's (2014) study verified previous unreliable suggestions about increased sales following natural disasters. Owners of flood affected homes in higher-value neighbourhoods tended to rent other accommodation and repair their own homes instead of putting their damaged properties on the market. However, in the lower-value neighbourhoods, a greater number of flood damaged homes were listed for sale rather than being repaired.

The recovery outcomes in each neighbourhood represent important aspects of disaster resilience. To address how recovery proceeded after the flood, a series of recovery outcomes were investigated based on the data available for the study area, including property listings for sale and rent as well as building approvals to track housing and construction activities after flood. Moreover, the number of displaced people and relocation survey data conducted by NCCARF is used in this study to assess the intention of residents to migrate from the neighbourhood (Bird et al., 2013b), and give estimates of overall recovery trends in the affected neighbourhoods of Brisbane and Ipswich. However, these recovery outcomes are not included in quantitative analyses due to the lack of precise data for all neighbourhoods in the study area.

In this research, Chapter 8 and Chapter 9 detail the reconstruction status which is used as recovery outcomes in each neighbourhood, and empirical real world evidence of neighbourhoods' resilience for validation of the resilience model. The methods used to collect and calculate the recovery outcomes are described in the following section.

4.3 Data Collection Methods

The 2011 Queensland flood and the subsequent recovery have been investigated by academics, government agencies and other organizations in several studies, therefore, data on the pre-disaster and post-disaster conditions and recovery are sporadically available. Data collection strategies in this research mostly consist of already existing survey data (obtained from government organizations and academic institutes), secondary/ archival data publicly available from different sources and an analysis of relevant governmental and organisational documents.

In this research, for the antecedent resilience conditions, mostly freely available secondary data sources are used deliberately so that the indicator set could be replicated with a reasonable amount of effort. These sources includes Australia Census data obtained from the Australian Bureau of Statistics, the National Exposure Information System (NEXIS), Spatial (GIS) data layers obtained from the Queensland Government's online database, properties sales and rental data obtained from RP database and some other data from Risk Frontiers Australia, Queensland flood relief report, Emergency Management Australia (EMA).

The data for recovery assessment are extracted from surveys such as DARMsys and ACCS which have been conducted by different organizations to capture the contextual complexity of the recovery. These data are obtained via contacts in the Reconstruction Authority of Queensland, The University of Queensland and the National Climate Change Adaptation Research Facility (NCCARF). Some of these datasets are discussed in detail below, and further sections of this thesis discuss ways in which these datasets are used to develop the dataset needed for this research.

4.3.1. NEXIS (National Exposure Information System)

The NEXIS dataset developed by the Exposure Information Section (EIS) and Risk and Impact Analysis Group (RIAG) at Geoscience Australia provides up-to date exposure information about Australia's resident population and buildings. These data are used for independent variables related to the built environment characteristics and the value of properties. These data were obtained from GeoScience Australia at the time of this research's analyses. The data are now freely available through GeoScience Australia's website.

The Department of Public Works (DPW) in Queensland was responsible for the building recovery, leading and coordinating the planning and implementation of all state-wide building reconstruction functions. The age and typology of buildings is a criteria used to assess infrastructure quality in neighbourhoods. Geoscience Australia's NEXIS dataset reports the number of houses in each neighbourhood built prior to 1980 and after 1981, as this marks a significant change in Australian building standards. The age of housing also could be an indicator of the architectural styles. Post 1980 homes are mostly constructed of brick veneer, on a cement slab on the ground. These buildings suffered more damage compared to the traditional Queenslander style buildings (Mason et al., 2012). Mason et al. (2012) showed that Queenslander style buildings were more resilient due to their elevated designs and resilient materials. In fact, their single skin walls were easier to clean and dried out quicker than those built with cavity constructions. The data from the NEXIS dataset show that the neighbourhoods with more buildings constructed after 1980 have a negative correlation with the damage level (-0.424, $p<0.05$) which could indicate the risk aware construction methods used after the 1974 flood in Brisbane.

4.3.2. Damage Assessment and Reconstruction Monitoring System (DARMsys)

The Reconstruction Authority of Queensland developed the Damage Assessment and Reconstruction Monitoring system after the 2011 flood in Queensland in order to monitor Queensland's rebuilding progress. The Reconstruction Authority's system for monitoring was through travelling street-by-street and house-by-house in flood affected communities to identify the damage and reconstruction status. DARMsys and associated flood mapping has been acknowledged by the World Bank as having played an instrumental role in providing quality information, enabling Queensland to recover quickly from the natural disasters of 2010-2011. This dataset provided the recovery outcome data for this research, such as initial damage levels and rate of reconstruction. The damage and reconstruction data for 76 flood-affected neighbourhoods of Brisbane and Ipswich are available and can be investigated for their recovery process.

Damage Assessment in Brisbane and Ipswich Neighbourhoods

As mentioned earlier, in Brisbane and its surrounds more than 14,000 properties were flooded. Physical damage is clearly a primary factor in explaining the level of recovery experiences. The percentage of the neighbourhood area that was flooded in 2011 is shown in Figure 4.4. North Booval (80%), Rocklea (79%), Fairfield (60%), Chelmer (58%), Tennyson (55%), Graceville (41%), Jindalee (38%), Goodna (31%), Oxley (38%) and Yeronga (33%) are among the neighbourhoods with a high percentage of flooded areas. Comparing the percentage of areas in each neighbourhood affected in the 1893, 1974 and 2011 floods shows that Chelmer and Graceville were severely affected by floods in 1893 and 2011, while in the 1974 flood only one percent of these suburbs were affected by flood water. This could have led to a misconception about their vulnerability, and the fact that people in these suburbs were less prepared for the 2011 flood, as they had not experienced the 1974 flood.

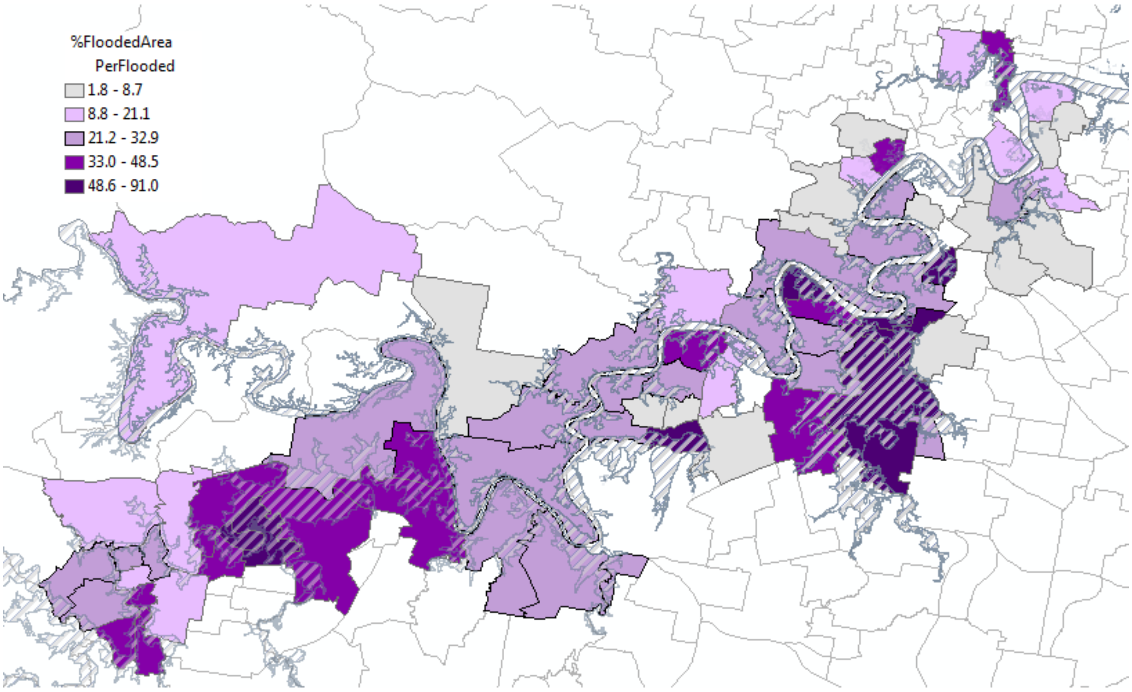


Figure 4.4. Percentage of flooded area in the Brisbane study area

Housing Recovery Progress over Time

Considering the scale of the analysis and data availability, the applicable recovery outcome indicator for this study is housing reconstruction progress, which is described and calculated below. Housing recovery could represent the return of a community's normal daily activities. It is one of the key dimensions of the recovery process which also influences other dimensions of recovery (Bolin, 1994; Comerio, 1998). DARMsys is used to track the reconstruction process in affected neighbourhoods spatially and temporally. Considering the nature of the available damage and recovery data, two alternative proxies have been considered for housing recovery. The first proxy is based on the level of change in the aggregated damage loss. As the reconstruction monitoring audits are conducted every three months, seven months after the flood for four rounds, we calculate the percentage of recovery within 10, 13 and 16 months after the flood, based on the formula below:

*% reconstructed after 10 months = (Damage loss 201107- Damage loss 201110)*100/Damage loss 201107*

The other proxy for housing recovery combines the damage level with the recovery level, which is called here the 'resilience index'. This variable has been defined as the area under the damage and recovery curve for each neighbourhood within the 2011/07 - 2012/05 timeframe. This area is calculated by summing up the areas of each trapezoid. As a zero area would be the indicator of least damage and the quickest recovery, the lower score means more resilience and therefore the calculated area is multiplied by (-1) to show the resilience level.

Recovery Index = (-1) $(D_1+D_2)/2+ (D_2+D_3)/2+ (D_3+D_4)/2= D_2+D_3+ (D_1+D_4)/2$

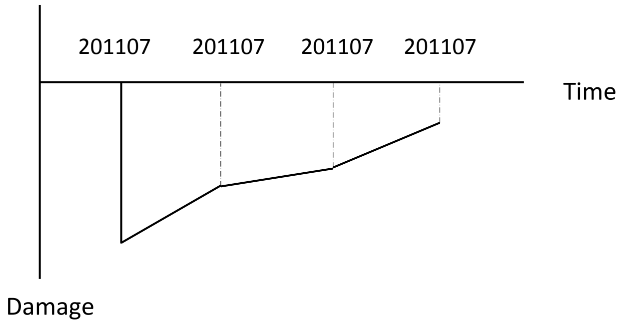


Figure 4.5. Recovery index representation

The maps below represent the housing recovery status within seven months (Figure4.6), ten months (Figure 4.7), 13 months (Figure 4.8) and 16 months after the flood (Figure 4.9). The darker shades show very limited recovery progress and the lighter shades show the fully recovered areas.

In the seven months following the flood, very limited recovery occurred in neighbourhoods with extensive damage, including neighbourhoods close to the river and those far from the river. The areas close to the flood lines showed very limited signs of housing recovery seven months after the flood.

Eleven neighbourhoods managed to completely reconstruct damaged properties within 10 months after the flood including the suburbs of Balmoral, Greenslopes, Hawthorne, Kangaroo Point, Kholo, Leichardt, Newstead, Pinjarra Hills, Sinnamon Park, Sumner and Walloon. These neighbourhoods are among the least damaged areas. Neighbourhoods such as Anstead, Moggill, Marburg and Calvert also are among the least damaged areas; however they had a much slower recovery rate comparing to the previously mentioned eleven neighbourhoods.

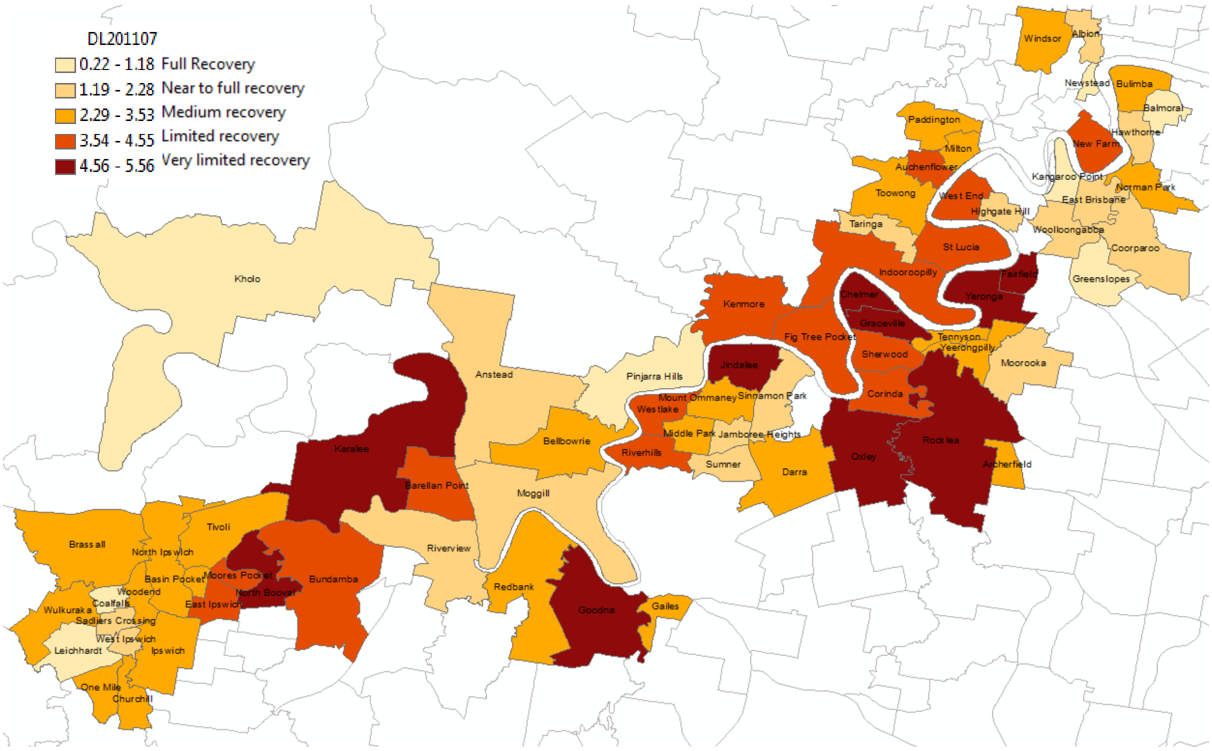


Figure 4.6. Spatial pattern of flood recovery in 07/2011

(Source: Author adapted from Reconstruction Authority of Queensland)

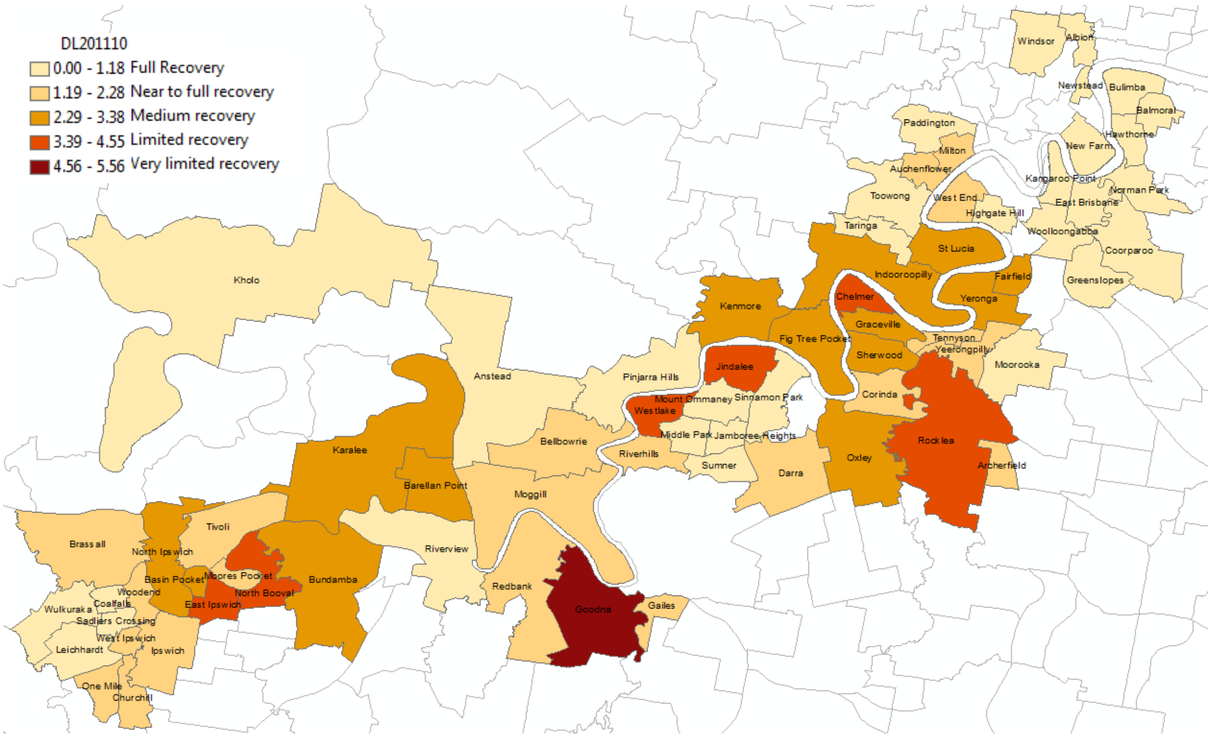


Figure 4.7. Spatial pattern of flood recovery in 10/2011

(Source: Author adapted from Reconstruction Authority of Queensland)

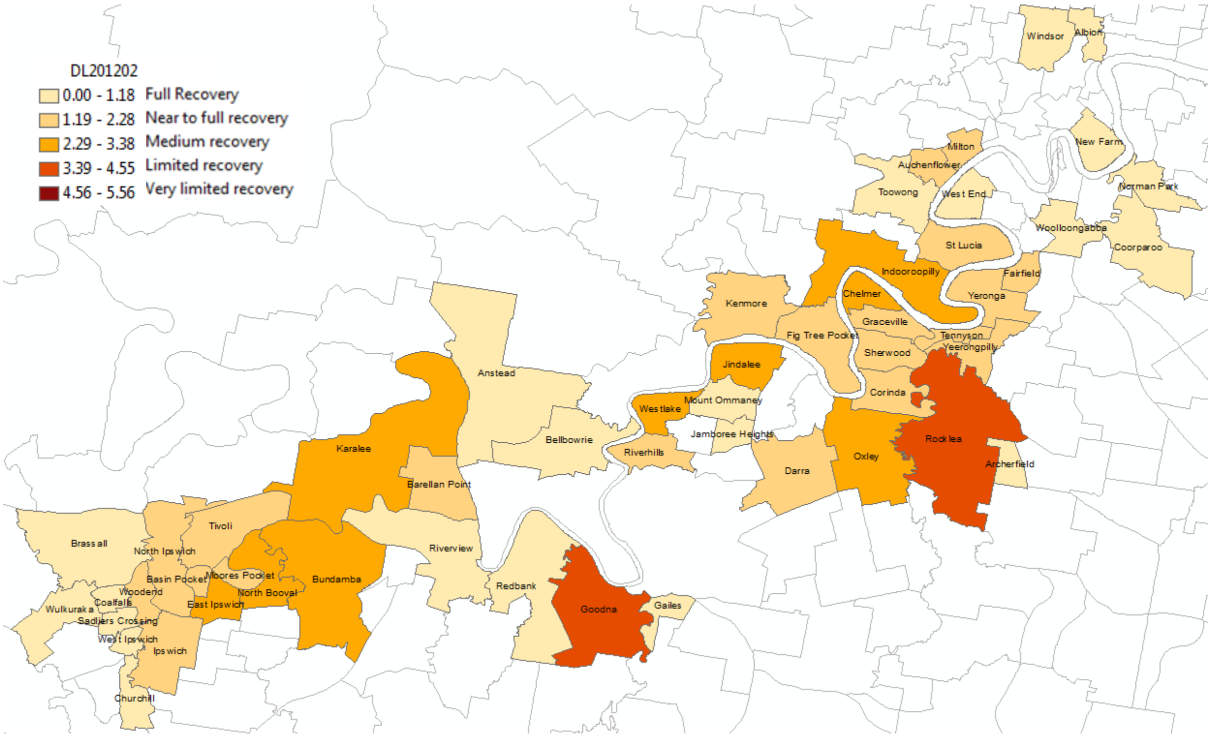


Figure 4.8. Spatial pattern of flood recovery in 02/2012
(Source: Author adapted from Reconstruction Authority of Queensland)

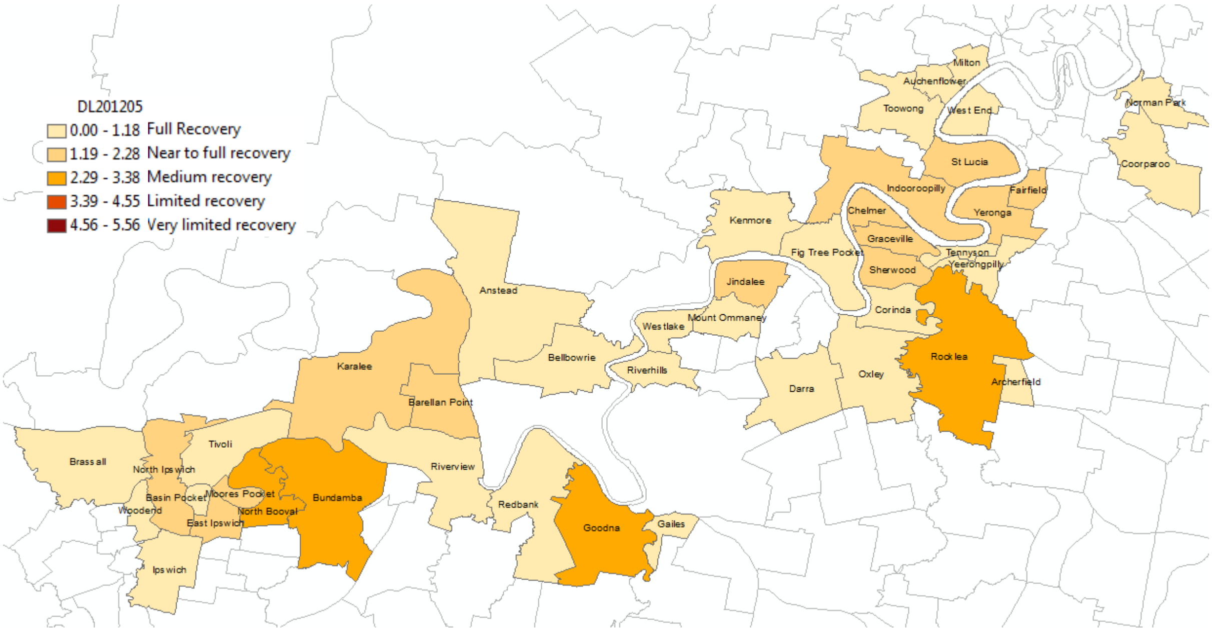


Figure 4.9. Spatial pattern of flood recovery in 05/2012
(Source: Author adapted from Reconstruction Authority of Queensland)

A visual assessment of these recovery maps presents a spatially variable recovery progress. Ten months after the flood, most of the neighbourhoods show a limited to medium recovery level (Figure 4.8) except for eleven neighbourhoods (Pinjarra Hills, Newstead, Kholo, Sinnamon Park, Hawthorne, Walloon, Balmoral, Kangaroo Point, Sumner, Greenslopes and Leichhardt). These neighbourhoods are mostly located in the eastern part of the city and sustained less damage than other neighbourhoods. On the other hand, most of the neighbourhoods with the least level of recovery are located in the western, low lying part of the study area close to Ipswich (East Ipswich, North Ipswich, Calvert, Goodna, Basin Pocket, Yeerongpilly, Westlake and Moggill). Of interest are the suburbs of Moggill and Calvert, which had very low levels of property damage and still showed very limited recovery ten months after the flood. Approximately the same sort of differential recovery is evident 13 and 16 months after the flood (Figures 4.11 and 4.12). The least recovered neighbourhoods after 16 months are generally those with a slow recovery rate at 10 months as well.

Fairfield for example, was among the most severely damaged neighbourhoods in Brisbane. Seven months after the flood, among the 511 affected properties surveyed in this neighbourhood, 123 were reconstructed and had no damage, 133 had minor damage, 74 showed a moderate amount of damage, 63 had severe damage and 118 properties were totally damaged.

4.3.3. Socio-Economic Indexes for Areas (SEIFA)

The Socio-Economic Indexes for Areas (SEIFA) is a census based index developed by the Australian Bureau of Statistics which ranks areas in Australia according to relative socio-economic advantage and disadvantage. It consists of sub-indexes: (1) the Index of relative Socio-Economic Disadvantage summarises variables that indicate relative disadvantage (2) the Index of Economic Resources focuses on the financial aspects of relative socio-economic advantage and disadvantage (3) the Index of Education and Occupation summarises variables related to educational qualifications. Different parts of this index are used in developing the Neighbourhood Disaster Resilience Index (NDRI), for example the third sub-index of SEIFA represents human capital in NDRI.

The Department of Communities (DoC) was responsible for social recovery after Queensland's 2011 flood and its aim was to restore and strengthen local human services and community capacity. In Chapter 5, various indicators are considered as contributors to social resilience, including the level of community participation, place attachment, social capital, etc. Jordan et al. (2014) emphasises the importance of community participation and social capital for successful population return. They showed that people with stronger attachment to place and social networks would be more likely to rebuild in the same location following a disaster. Also, they found that community participation is slightly more important to successful recovery than social capital, showing that post-disaster community participation might be able to stabilize the negative effects of not having strong pre-existing social links. However, the presence of relatively strong public institutions, including the emergency services, police and local government, guaranteed that the people without strong local networks would not be abandoned (Walters, 2015). Wickes et al. (2015) examined the effects of prior levels of social capital on community resilience after the flood in Brisbane. This was conducted through the residents' ratings on seven different incivilities in their communities. They found that community problems are significantly lower in flooded communities compared to non-flooded communities. Also they found that, in general, a higher level of social capital is associated with fewer community problems.

In order to find out how much time the people of a neighbourhood have spent helping others after the flood, the data from the Censuses of 2006 and 2011 on the level of participation in each neighbourhood are used in this research as one of the social resilience attributes of the neighbourhoods. More specifically, it can be said that the Mud Army, a community participation initiative in Brisbane, played an important role in preparedness and recovery after the flood and this was critical in sustaining the recovery efforts. The Mud Army helped in different aspects of preparedness, protection (including sandbagging the properties in danger, removing contents of homes in danger); response and recovery (including feeding people and animals, cleaning, debris removal, etc.). This pro-social behaviour post disaster is a known phenomenon called altruistic/therapeutic community which states that the majority of people behave in rational and constructive ways immediately following a disaster (Bruneau et al., 2003).

The Brisbane flood was not a catastrophic disaster which had a huge displacement impact. However the temporary displacement of some people in severely affected neighbourhoods is reported in some studies after the flood (Bird et al., 2013b; Mason et al., 2012). Bird et al. in their post flood survey asked if householders had returned to their houses permanently at the time they conducted the survey, eight months after the flood. The sample size in this survey is not large enough to generalise the results, but within the four neighbourhoods investigated in this survey, Rocklea had the least population return, the least completed reconstruction and the highest income interruption eight months after the flood.

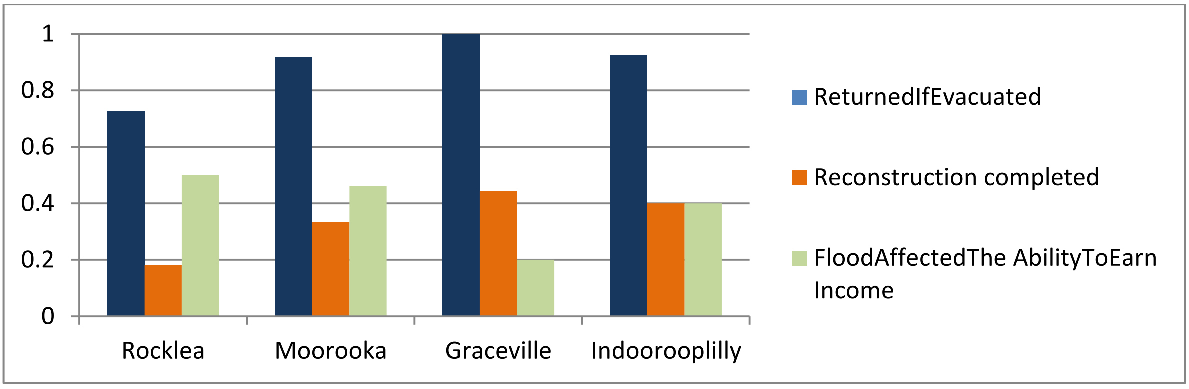


Figure 4.10. Population returned to their houses, reconstruction completed and impact on income in four neighbourhoods of Brisbane (Source: NCCARF Brisbane flood survey data)

Kates et al. (2006) claim that historical evidence shows that recovery after a disaster usually follows the pre-disaster trajectory, with the disaster even accelerating previous trends. In cities with growing populations and economies, the disaster may accelerate that growth; whereas for cities in economic and social decline, the disaster may speed up decline, similar to New Orleans, USA after Hurricane Katrina in 2005. However, in the case of the Brisbane flood, the population showed an increase in the first year after the flood, despite the previous declining population trend. According to ABS data, after the Brisbane flood between 2011 and 2012, the population of Brisbane grew by 2%, slightly higher than average for Australia's capital cities (1.8%) and higher than for the remainder of Australia (1.2%). The suburbs of Redbank (6.6), Woolloongabba (5.2), Bulimba (4.2), Brassall (3.9), Hawthorne (3.9), Saint Lucia (3.9) and Greenslopes (3.8) show the highest population growth within the first year after the flood. While in the second year after the flood, Woolloongabba (7.7), Fairfield (7.4), Goodna (5.1), Redbank (4.4), Milton (4.4), Paddington (4.4) and New Farm (3.6) show the highest levels of population growth.

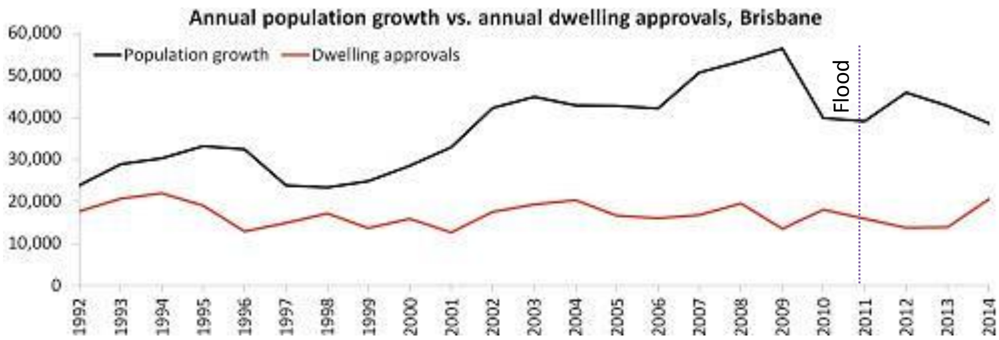


Figure 4.11. Annual dwelling approvals (Source: RP data)

A large body of research has focused on how social vulnerability influences recovery patterns (e.g. Bolin, 2006; Cutter et al., 2003; Finch et al., 2010; Fothergill et al., 1999; Tierney, 2006). Socially vulnerable populations may be more likely to live in hazardous locations, less able to access services after a disaster, and less likely to have resources for rebuilding. In this study, social vulnerability is assessed based on the established SoVI index introduced by Cutter et al. (2006).

Social vulnerability is measured by a number of demographic indicators, which many researchers have linked it to overall resilience (Cutter et al., 2003; Tierney, 2006; Wisner, 2004). Among the nine most severely damaged neighbourhoods, Chelmer, Graceville and Jindalee have the lowest SoVI while Goodna is the most socially vulnerable neighbourhood, followed by Moorooka, Fairfield and Rocklea. Goodna, as the most socially vulnerable neighbourhood, shows the least progress in reconstruction. However, the SoVI does not show any strong association with the reconstruction progress, as Chelmer and Jindalee, with low levels of SoVI, do not show a better performance compared to other neighbourhoods with higher SoVI. Overall, as Jordan et al. (2014) suggests, in this case high social vulnerability is sufficient but it does not necessarily lead to slow recovery.

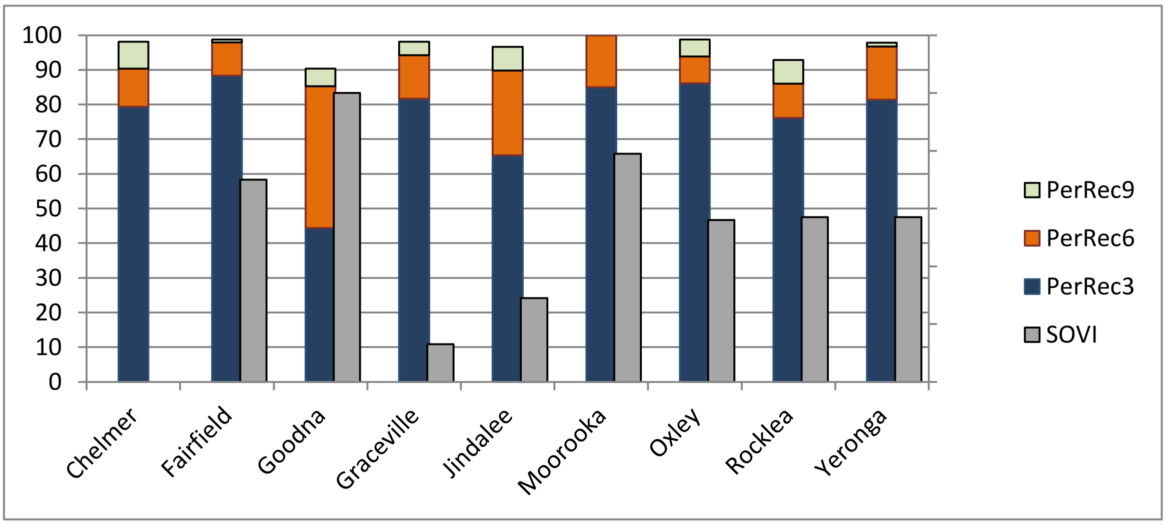


Figure 4.12. Normalized percentage of reconstruction progress compared with the level of SoVI for the nine most severely damaged neighbourhoods in Brisbane

(Source: Reconstruction Authority of Queensland and Australian Bureau of Statistics)

4.3.4. Australian Community Capacity Survey (ACCS)

The Australian Community Capacity Survey (ACCS) is a longitudinal panel study of urban communities in Australia, which is supported by the Australia Research Council (Wickes et al., 2015). The main goal of the ACCS was to understand the key social processes associated with the spatial and temporal variation of crime and disorder across urban communities. However, shortly after the third wave of ACCS data was collected in late 2010, the Brisbane 2011 flood occurred and more than 150 neighbourhoods across Brisbane were inundated to varying degrees. Forty three of these neighbourhoods are included in the ACCS and therefore in wave four of the ACCS, a section related to flood coping capacity was incorporated into the ACCS's questionnaire. In this research, financial assistance data are used to assess the post-disaster conditions. It should be noted that, as illustrated in Figure 4.13, the overlap of ACCS and DARMsys consisted of 26 neighbourhoods which defined the number of cases in the comparative analysis of recovery pathways after the flood.

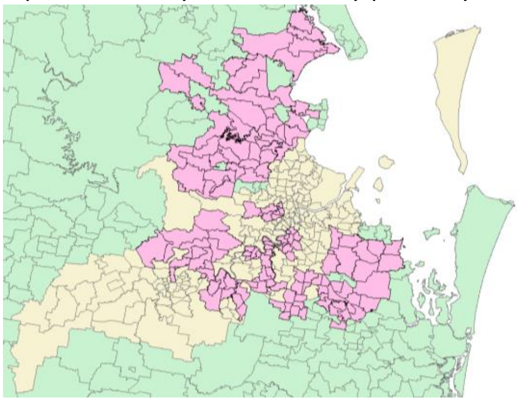


Figure 4.13. Neighbourhoods included in ACCS (147)

According to the Queensland reconstruction framework (Government, 2011), the available resources for reconstruction consisted of federal resources, state resources, local government efforts, not-for-profit assistance, corporate assistance and international assistance. The data for federal, state and local assistance are present in the ACCS dataset and are used in this study as post-disaster conditions of neighbourhoods in the study area. According to the ACCS dataset, Mount Ommaney and Jindalee received the highest level of state financial assistance, while Moorooka, Greenslopes, Yeerongpilly, Jamboree Heights, North Ipswich, Sinnamon Park and Paddington received the least state financial assistance. The number of 'state financial assistance' receivers has a significantly correlated relationship with the number of successful insurance claims in each neighbourhood. Karalee, Tennyson, Barellan Point and Fairfield received the largest proportion of federal assistance while Yeerongpilly, Moorooka, Corinda, Anstead and Greenslopes received the lowest amount of federal assistance.

The number of successful flood insurance claims left many affected people in the Brisbane and Ipswich areas dissatisfied. According to Lo's study (2013), about 33% of the survey respondents thought that their insurance covered them for all types of flood. This percentage was even higher for those with incomes over $100,000 (57%). These higher income residents also did not qualify for state financial assistance while they lost a great part of their annual income due to their businesses suffering flood damage. Their insurance companies did not pay out for the damage they suffered, and they were unable to afford to repair their homes. The major criticism of government compensation schemes was that they provided perverse incentives for privately managing hazard risks. The ACCS survey results from flood affected residents of Brisbane showed that only 109 out of 1,915 respondents said that their insurance claims were successful. Insurance has correlations with damaged .423**, moved .325**, financially affected .166** at an individual level.

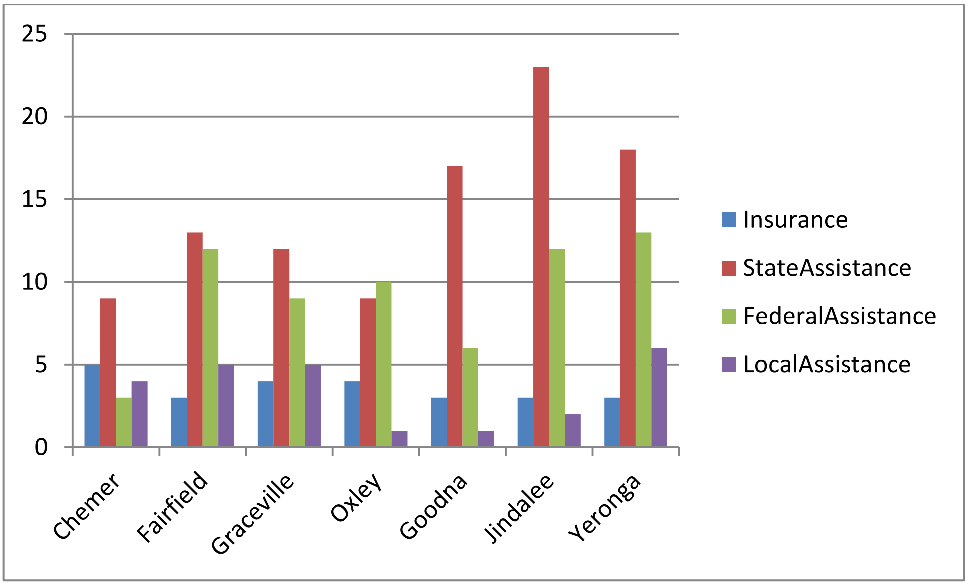


Figure 4.14. The relative distribution of financial resources in most severely damaged neighbourhoods

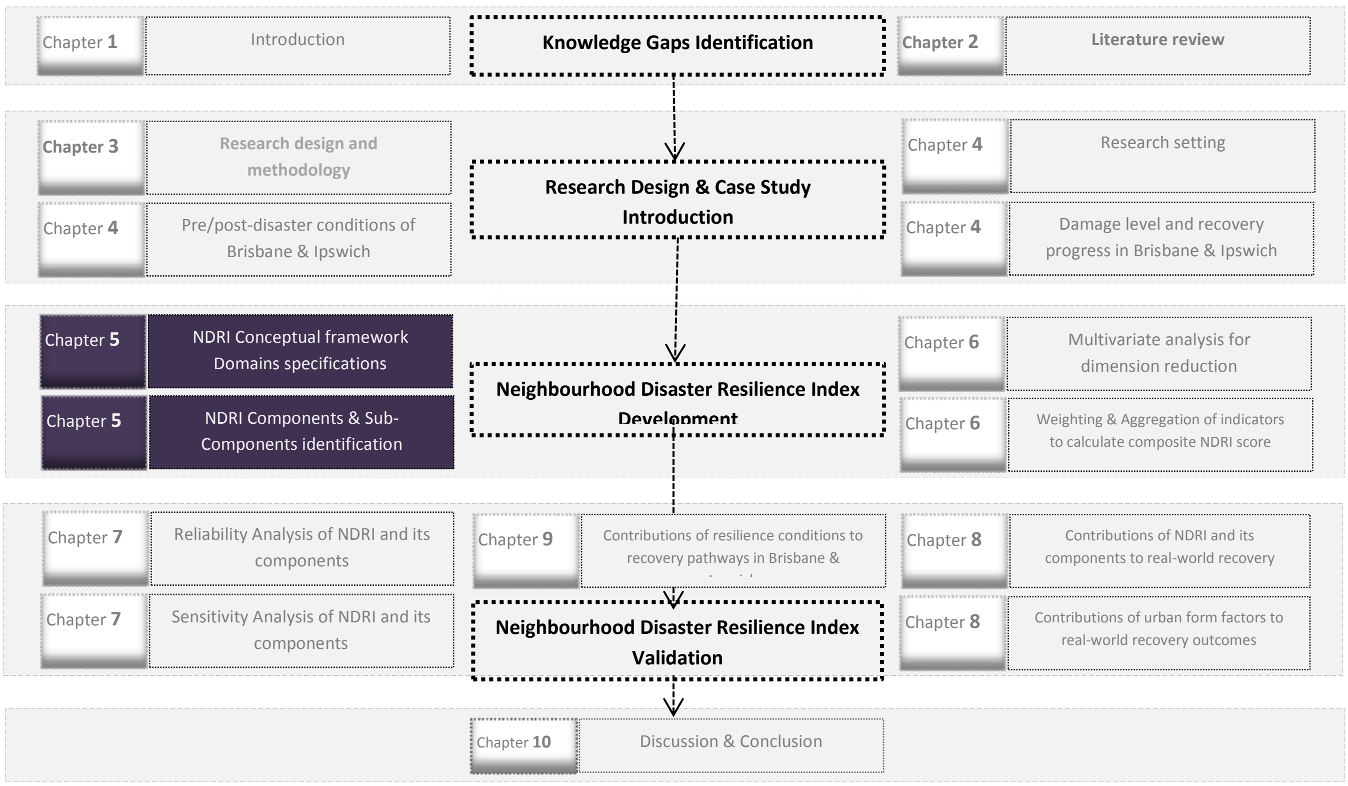
(Source: Australian Community Capacity Study survey (ACCS))

4.4. Summary

In this chapter, the case study utilised in this research to validate the proposed model (NDRI) is introduced. The research setting is explored by reviewing the case study area; the disaster affected area in 2010/2011, the data sources and the conditions and recovery process in the affected neighbourhoods.

Chapter 5
Index Development

Theoretical Framework and Indicators Selection



5. Index Development - Theoretical Framework and Indicators Selection

5.1. Overview

This chapter sought to answer the first set of research questions for this study including:

Research questions

- What is the nature of the resilience construct's conceptual domains and properties?
- What are the key indicators of disaster resilience at neighbourhood level?

Methodology

As elaborated in Chapter 3, the research questions of the study to a great extent define the methods employed and the type of findings that are desirable. In order to answer the first question, a theoretical framework is developed based on the thematic analysis of urban resilience literature and by examining previous models on resilience, vulnerability and adaptation capacity. The theoretical framework presents the definition, conceptualisation and specifications of the resilience model in this study. The components of resilience and the indicators representing these components are analysed using a cross-classification method to address the second question.

5.2. Theoretical framework for indicators selection

The development of a comprehensive theoretical framework in the early stages of index development provides an understanding and definition of the phenomena. This also offers the means of combining these individual indicators into a meaningful composite index by serving as a basis for variable selection, weighting and aggregation.

5.2.1. Working definition of resilience

Urban resilience is to some extent an abstract and latent characteristic of an entity rather than a concrete and observable attribute. Thus, according to Nunnally et al. (1967), the intended model in this study is a "construct", and as such, a resilience index is literally something that we "construct" and which does not exist as an observable and directly measureable attribute of an entity.

Therefore, for the first step the definition of the conceptual domain of the resilience construct is necessary in order to prevent confusion about what it does and does not refer to (Meerow et al., 2016). Table 2.1 in Chapter 2 – as part of an extensive literature review - offered a summary of the variety of the definitions offered for the resilience construct in the previous research. Nevertheless, considering that the focus of this dissertation is on built environment resilience at the neighbourhood level, neighbourhood disaster resilience is defined as:

> *The capacity of community and its built environment at neighbourhood scale to absorb the impacts of disaster and recover in a timely manner after disaster, in order to reach and maintain an acceptable level of function and structure, while learning from past incidents.*

This definition is compatible with the scope and scale of the intended model in this research, which is focused on the neighbourhood level. 'Learning from the past' is a critical part of this definition, as previous studies (Alam et al., 2008; Drupsteen & Guldenmund, 2014) have shown that learning from the past increases communities' preparedness for and mitigation level of disasters. It should be mentioned that the outcome oriented definition of resilience is intentional, as it is appropriate for measurement modelling. In fact, it defines resilience in terms of the end results, such as degree of recovery, time to recovery or extent of damage avoided. This definition facilitates the validation process by offering two notable real-world outcomes, including impact level and recovery capacity.

5.2.2. Conceptualisation of resilience in this study

In order to build the conceptual framework, a critical review of the literature and a systematic analysis of the existing models were conducted (Irajifar et al., 2013). This method, in fact, was a thematic analysis of the literature to extract the key components and concepts related to resilience (see Chapter 2). Each of these concepts possesses its own attributes, characteristics, distinct perspectives and specific functions within the conceptual framework.

In this research, with recognition of the contributions from existing models and also their limitations, three notions are found appropriate to conceptualize resilience within a framework: 1) resilience attributes, 2) resilience components and 3) the 'impact absorbent' and 'quick recovery' notions. These three notions are introduced in Chapter 2. The conceptual framework of this research (as shown in Figure 5.1) argues that the ability of urban systems to deal with disasters is based on their capability to absorb the disaster impact and recover in a timely manner after the disaster. On the other hand, resilience attributes are viewed as defining characteristics of resilience which can confirm the strength, capacity, and resources that enable a community to absorb the disaster impacts and quickly recover.

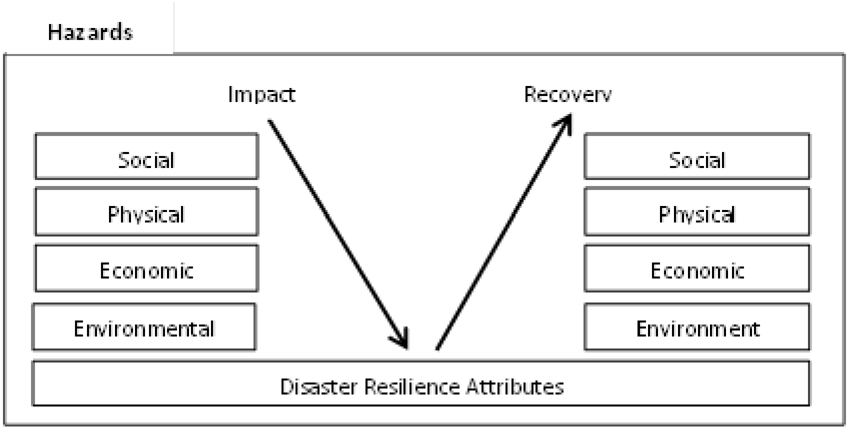


Figure 5.1. Conceptual framework for measuring disaster resilience

The focal construct in this research is a function of the resilience attributes within each component. Considering its multidimensionality and complicated nature, further specifications of the intended model are discussed in the next section.

5.2.3. Specifying the resilience measurement model

In moving from a definition of resilience to measuring it, the general properties that the intended resilience construct refers to should be specified as a necessary step in precisely specifying the nature of the construct (MacKenzie et al., 2011). The general property that resilience construct intends to refer to in this research is the 'capacity of absorbing the impact and recovering quickly'. The entity this construct aims to refer to is the urban system at neighbourhood level.

5.2.3.1. The dimensionality of the resilience model

Now that the resilience construct has been carefully defined, it is important to step back and evaluate whether there are multiple sub-dimensions of urban resilience, and how they relate to the focal resilience construct and to each other. Given the multi-dimensionality of urban systems, which is the entity that this construct refers to, it can be concluded that urban resilience is a multi-faceted concept. There is a consensus within the research community that urban disaster resilience includes social, economic, institutional, environmental and built environment components (Bruneau et al., 2003; Cutter et al., 2008; Cutter et al., 2010; Gunderson, 2010). Since the unit of analysis in this study is the neighbourhood, the institutional component has not been considered in this study as it would have the same value for neighbourhoods in the same local government area. However, in the case of comparing neighbourhoods from different local government areas, a dummy variable will represent the effect of the institutional capacity of each local government area on the disaster resilience of neighbourhoods. It is important to note that not considering institutional resilience in this model does not mean that it is less important in building disaster resilience at the neighbourhood level, but its effect would be for the whole local government area (LGA).

On the other hand, the dimensionality of the resilience construct stems from the two distinctive essential characteristics of resilient urban systems, which have the ability to 'absorb the impact' and 'quick recovery to the previous level of function'. Eliminating either of these components would restrict the conceptual domain of the construct; therefore, the intended model in this research is a multidimensional model of resilience which consists of a number of interrelated attributes and dimensions, including social, economic, environmental and physical components.

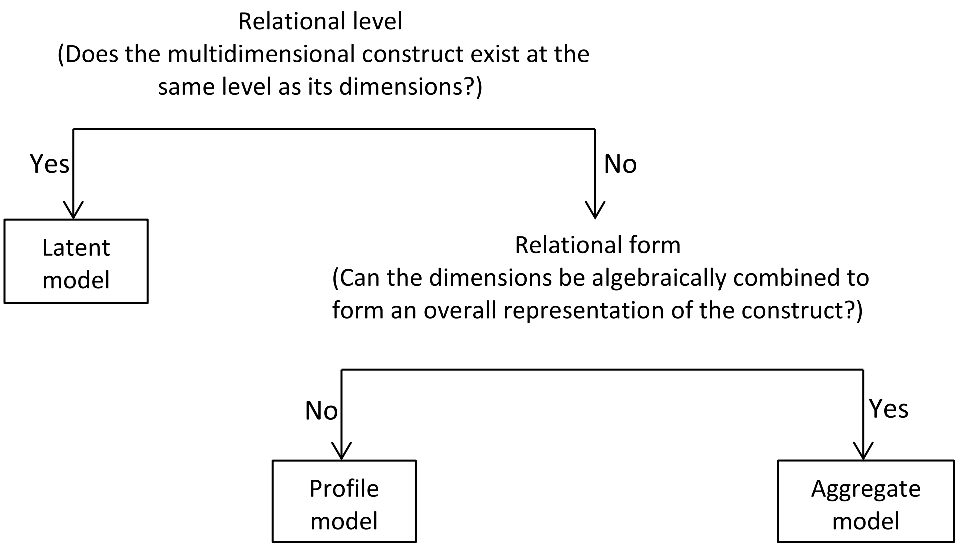


Figure 5.2. Taxonomy of multidimensional models

(Law et al., 1998)

Law et al. (1998) argue that the nature of a multidimensional construct differs when different interpretations are attributed to the relations between the overall construct and its dimensions. They classify multidimensional models into latent models, profile models and aggregate models (Law et al., 1998). In the latent model, the dimensions are simply different forms of the manifestations of the focal construct, which means that the construct leads to the dimensions, whereas the aggregate construct is formed from its dimensions. Therefore, the overall latent model is the latent commonality underlying the dimensions, whereas in the aggregate model the overall construct is the mathematical composite formed from dimensions. On the other hand, a profile model can be interpreted as a set of profiled characteristics of the dimensions, and there will not be a single theoretical overall construct that represents all the dimensions.

In the latent model, only the common variance or the covariance shared by all dimensions is considered as true variance of the construct, and the specific variance and group variance and random variance is treated as error variance (Figure4.3). Under the aggregate model, only the random variance is considered as error variance and all other specific, group and common variances are actually the true variance of the construct (Nunnally et al., 1967).

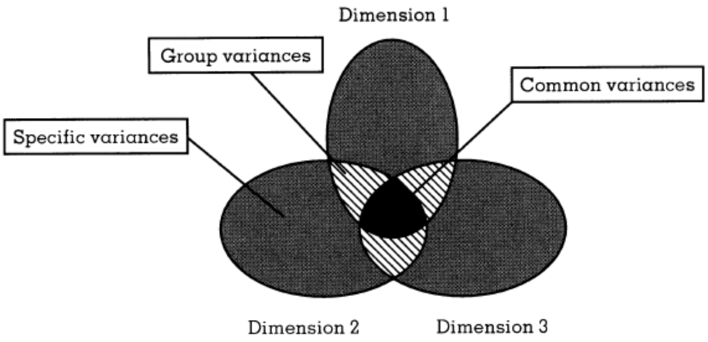


Figure 5.3. Different types of variances in multidimensional constructs

The focal resilience construct intended in this study exists at the same level as its dimensions. The aggregation of the dimensions can form and represent the overall resilience capacity of the urban systems. Given the purpose of this model, the intended model in this research is an aggregated model which is also called a composite indicator. Composite indicators are much like mathematical or computational models. As such, their construction owes more to the skills of the modeller than to universally accept scientific rules for encoding.

5.2.3.2. Formative vs. Reflective: Defining the relations between the construct and its dimensions

The distinction between formative and reflective measurement models is critically important in the first step of the construct development (Coltman et al., 2008). The majority of the scale development techniques suggested in the literature only relate to the latent constructs with reflective indicators, and if they are applied to the latent constructs with formative indicators, they might undermine construct validity. For instance, the literature on scale development mostly recommends that items with low item-to-total correlations should be eliminated from a scale to enhance internal reliability. This recommendation is applicable in the case of reflective indicators, as the items are all from the same content domain, but if it is followed for constructs with formative indicators, it may result in the elimination of exactly those items that are most likely to adjust the empirical and conceptual meaning of the construct. Thus, as noted by MacKenzie et al. (2011), the next step in developing the construct is to specify the relationships between the indicators and the focal construct and/or sub-dimensions they are intended to represent.

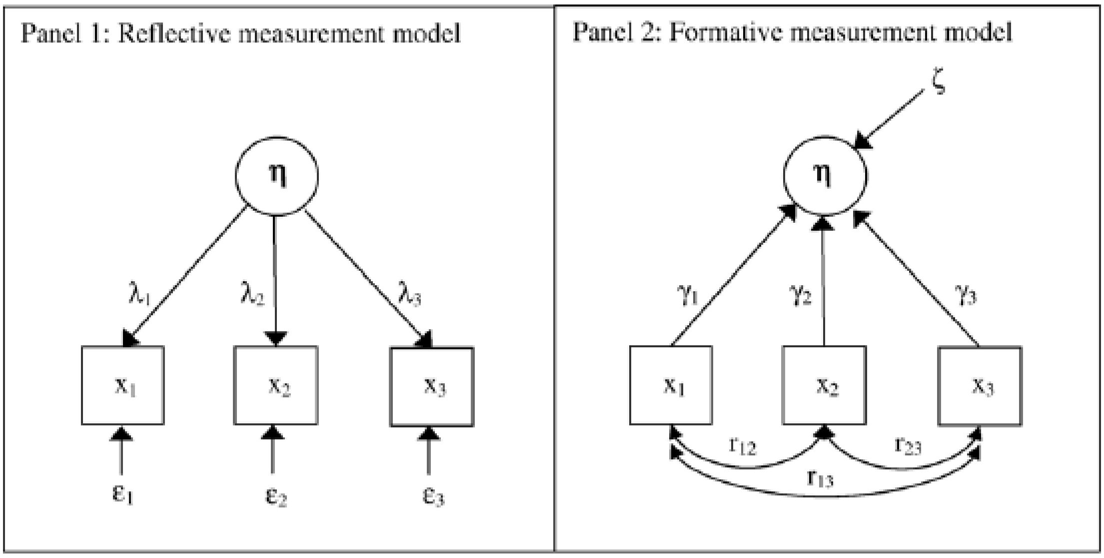


Figure 5.4. Alternative measurement models

Three broad theoretical considerations are important in deciding whether the resilience measurement model is formative or reflective. First of all, the nature of the resilience construct is formative, as resilience does not exist in an absolute sense independent of the measures. A formative resilience construct is a composite measure of resilience components, and any changes in one or more of these components will be likely to cause a change in construct score. For example, an increase in quick recovery capacity might be associated with an increase in resilience level, without necessarily being associated with any changes in the capacity of an urban system to absorb the impacts of a disaster. This is because of the fact that absorbing the impact is related to the exposure of urban assets to disasters, while a quick recovery is more related to the coping capacity of urban systems. For example, an increase in the level of average income in a neighbourhood might be associated with an increase in that neighbourhood's disaster resilience level, without necessarily being associated with any changes in the neighbourhood's physical resilience.

The second theoretical consideration in deciding whether the measurement model is reflective or formative was the direction of causality. In this case, it flows from indicators to the resilience construct, in which a change in the indicators results in a change in the construct. This distinction of causality direction has a profound implication for measurement error and model estimation. The last theoretical consideration in determining whether the resilience construct is formative or reflective is the characteristics of indicators. In fact, in contrast to indicator interchangeability in reflective models, the domain of construct in formative models is sensitive to the number and types of indicators representing the construct. In this case, since all indicators do not share a common theme and are not interchangeable, the construct has been considered as formative. For example medical capacity and transportation capacity could not be sampled from a common domain and they are not interchangeable. Based on these theoretical deliberations in the proposed model, the nature of the construct, the direction of the causality, and the characteristics of the items used to represent the construct, it is best to conceptualize the NDRI model as being a formative model.

There are a couple of issues with formative models which need to be addressed before further steps in modelling are taken. First is the need to set the scale of the measurement and to ensure that the parameters of the model are all identified. The scale of the measurement can be set by, 1) fixing a path between the second order construct and one of its sub-dimensions at 1.0, or 2) by fixing the variance of the second order construct at 1.0. The second issue is to identify the construct level error term. In rare cases it might be a good idea to solve this by fixing the error term at zero. It is appropriate to fix the error term associated with the second order latent construct at zero if the first order indicators of the second order composite latent construct are free of measurement error. The next decision that needs to be made when specifying a construct with formative indicators is whether to freely estimate the covariances among the formative indicators and between these indicators and other exogenous variables. MacKenzie et al. (2005) recommend estimating the covariances among the formative indicators of the construct.

Resilience construct in this study is an exogenous second order construct with multiple first order sub-dimensions as formative indicators, and with multiple reflective indicators of each first order sub-dimension (Figure 5.5). To make sure that the parameters of the model are all identified, it is appropriate to fix the error term associated with the second order latent construct at zero provided that, 1) the first order indicators of the second order composite latent construct are free of measurement error; 2) all of the essential sub-dimensions of the second order construct are represented; and 3) the sub-dimensions do not interact with each other.

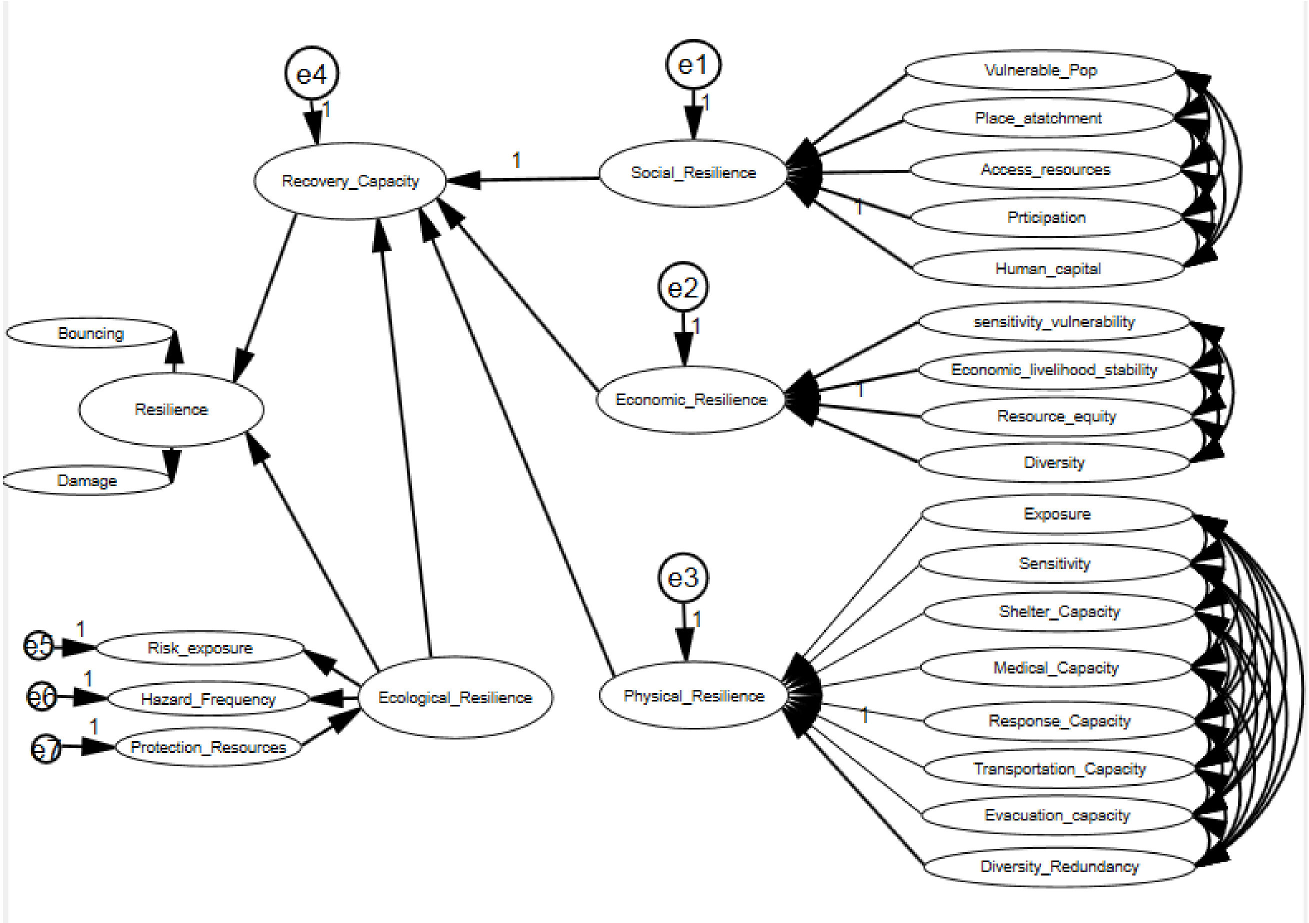


Figure 5.5. Path diagram showing the structure of NDRI and the relations between its dimensions

5.3. Identification of indicators for each sub-component

Once the conceptual domains of the resilience construct are carefully defined, the next step is to identify a set of indicators that perfectly characterize these domains. The research method for this step is mainly based on the combination of the critical review of the literature and a systematic analysis of existing models, using thematic analysis to find out the key conditions of resilience at the neighbourhood level. Table 5.1 shows the matrix that is used to guide the indicator selection process, which provides a matrix of resilience attributes within each resilience component. Based on the proposed framework and this matrix, disaster resilience indicators were identified by cross-classifying the four dimensions of resilience by resilience attributes, as discussed in Chapter 2. Choices among indicators were guided by a set of criteria: the variable should be justified in the literature, have consistent quality data, and also be scalable or available at different scales.

The focus of this study is more on improving the indicators of the built environment component, which is the least studied component in comprehensive urban resilience models. The indicators for built environment resilience were identified deductively by examining the resilience attributes in the physical elements of urban systems to create a platform on which built environment disaster resilience indicators could be developed. In fact, in this study the resilience attributes are important criteria for measuring the disaster resilience of each component, which can confirm the strength, capacity, and resources that enable urban systems to react resiliently in the event of a disaster.

The definition of each sub-component has been examined in the following sections with the same care that was used in the case of the focal construct itself. Basically, the cross-classification method was used to identify resilience attributes important in each component of the urban resilience. This study took a theoretically driven approach by identifying the main attributes of resilience in each component, then specifically identifying the indicators for each of these resilience attributes in each dimension. Taking this approach in developing the index, the indicators were selected inductively by 1) developing the sub-indices for each resilience component; and then 2) variables were collected for each sub-component as proxies for resilience, since it is often difficult to measure resilience in absolute terms (Cutter et al., 2008; Cutter et al., 2010; Schneiderbauer & Ehrlich, 2006).

Table 5.1. Cross-classification matrix of resilience attributes and urban system components

	Resilience attributes	**Physical**	**Social**	**Economic**	**Environmental**
Disaster impact	Robustness newer structures built to codes /regular maintenance)	· Exposure of buildings and lifelines exposure · Building and lifelines age, type, elevation …	· Population need no assistance · not vulnerable population …	· Exposure commercial buildings and industrial buildings …	% land in flood zone areas …
Capacity to response and recovery	Redundancy (capacity for technical substitutions; workarounds) …	· Alternative capacity for supply of water, electricity, sanitation (and solid waste disposal), · Alternative transportation & communication Substitutability	· Single parent families	· Per capita household income · Median income	
	Resourcefulness (robust critical facilities, availability of materials, skills for restoration)	· Medical capacity · Sheltering capacity · Response capacity (fire, police, SES stations) …	· Volunteering · Participation · Communication …	· Financial and insurance services …	% does not contain impervious lands …
	Density and diversity Modularity and independence (system independency)	· Accessibility to resources · Land use mix (LUM) · Dwelling density …		· Density of commercial infrastructure …	

5.3.1. Social indicators

The social resilience captures the capacity of communities during a disaster to effectively manage the negative effects and have the individual and social resources to recover quickly after a disaster (UNISDR, 2005). Thus at individual level, the literature in the field of social capital suggests that some demographic attributes of communities can enhance their social capacity in terms of their response to disasters. Communities with lower levels of minority residents, fewer elderly people, fewer people with disabilities, and fewer people speaking English as a second language are normally more resilient than communities without these characteristics (Cutter et al., 2010). On the other hand, communities with more skilled individuals in critical areas (such as health care and social assistance, construction services or lifeline services) have more resources and capacity in dealing with disasters. Thus, at individual level in measuring social resilience, it is important to identify characteristics of vulnerable populations and coping capacity, access to resources and human capital.

At social group level, attributes which facilitate cooperative actions can influence social resilience. This provides a safety net for people in the event of a disaster and can facilitate people's access to resources for disaster response and recovery (Dynes, 2002; Dynes, 2005; Lindell & Prater, 2003). Additionally, various research in this field has revealed that in situations where social capital or connectedness are lacking in a community, the people in that community are likely to have less capacity in the sense of networks for dealing with disasters (Societies, 2004). Putnam (2001) suggests measuring social capital by using composite indicators containing measures of participation and involvement in social groups, civic engagement and place attachment.

Nonetheless, social resilience indicators in this research have been developed based on the impact of disasters on the social fabric and the capacity of a community to respond and recover quickly after a disaster using the following six components suggested in the literature.

Table 5.2. Indicators identified for the social dimension of disaster resilience

Component	Indicator	Effect direction	Justification	Data source
Disaster impact on human capital & social fabric	**Vulnerable population**			
	% population aged > 5 and <65	+	(Cutter et al., 2010)	Census 2011
	% population not needing assistance	+	(Cutter et al., 2010)	NEXIS
	% renter renting public housings	-	(Cutter et al., 2010)	Census 2011
	% non-single parent family- family composition	+	(Rubinoff & Courtney, 2007)	Census 2011
	% not one person households-family composition	+	(Rubinoff & Courtney, 2007)	Census 2011
	% not large families- family composition	+	(Rubinoff & Courtney, 2007)	Census 2011
	% woman- gender	-	(Cutter et al., 2008)	Census 2011
Capacity of community to respond and recover quickly	**Place attachment**			
	% residents moved more than five years ago	+	(Cutter et al., 2010)	Census 2011
	% home owners occupancy	+	(Cutter et al., 2010)	Census 2011
	% immigrants arrived before last two years	+	(Cutter et al., 2010)	Census 2011
	Access to resources			
	% education higher than year 8	+	(Cumming et al., 2005; Cutter et al., 2003)	Census 2011
	% population with sufficient English	+	(Cutter et al., 2003; Cutter et al., 2010)	Census 2011
	Participation			
	% population doing voluntary work for an organization or group	+	(Cutter et al., 2010)	Census 2011
	% population volunteer	+	(Mayunga, 2009)	Census 2011
	% population doing unpaid assistance to a person with disability	+	(Cutter et al., 2010)	Census 2011
	Human Capital			
	Human capital index (SEIFA)	+		Census 2011
	% health care employees	+	(Cutter et al., 2003; Mayunga, 2009)	Census 2011
	% construction employees	+	(Mayunga, 2009)	Census 2011
	% finance and insurance employees	+	(Mayunga, 2009)	Census 2011
	% manufacturing employees	+	(Dynes, 2005; Mayunga, 2009)	Census 2011
	% transportation employees	+	(Mayunga, 2009)	Census 2011
	% electricity, gas, water, waste management employees	+	(Mayunga, 2009)	Census 2011

5.3.2. Economic Indicators

Rose (2007) defines economic resilience as the ability of economic systems within the urban systems to maintain function when shocked. Economic resilience can take place at three levels of economic systems: microeconomic (individual behaviour of households and firms), mesoeconomic (economic sector and cooperative groups) and macroeconomic (all individuals and markets combined and their interactive effects). In an engineering based approach, four attributes of resilience are sought in an urban economic system: 1) robustness (loss avoidance), 2) redundancy (untapped or excess economic capacity), 3) resourcefulness (stabilising measures), and 4) rapidity (optimizing recovery time)(Rose & Krausmann, 2013). In this research, however, economic capital basically represents the financial resources that people use to support themselves. The importance of economic capital in building community disaster resilience has been considered straightforward in the sense that economic resources increase the ability and capacity of individuals, groups and communities to absorb disaster impacts and to speed up the recovery process. The next sub-component of economic resilience considered in this study is resource equity, as people with access to financial resources recover more rapidly from disasters (Mileti, 1999). Also access to credit and hazard insurance are associated with the level of household preparedness and ability to take protective measures (Lindell & Prater, 2003).

Economic diversity is assumed to improve economic resilience for three reasons: 1) by controlling the impacts of shocks because the affected industry is a smaller portion of the local economy and the risk is distributed more widely (Frenken et al., 2007), 2) Provides opportunities for temporary income making alternatives (Izraeli & Murphy, 2003; Mizuno et al., 2006), 3) diversity improves skill matching between employers and employees, augmenting production efficiency, and alleviating frictional unemployment (Xiao & Drucker, 2013). There may also be drawbacks to diversity, such as insufficiently specialized labour skills or diverting attention from industries generating specialization advantages. However, it benefits many aspects of economic performance, including productivity, innovation, firm survival and income and employment growth (Beaudry & Schiffauerova, 2009; Renski, 2011; Xiao & Drucker, 2013).

Therefore exposure, sensitivity of economic assets, economic and livelihood stabilities, economic diversity and resource equity are the sub-components which best define the economic resilience of urban systems in this study.

The metrics for measuring these sub-components at the neighbourhood level are shown in Table 5.3. They are mostly extracted deductively for these sub-components and also from the Economic Vulnerability Index (EVI) (Briguglio et al., 2009; Guillaumont, 2008).

Table 5.3. Indicators identified for economic dimension of disaster resilience

Component	Indicators	Effect direction	Justification	Data source
Economic Impact	Exposure			
	Percent of commercial buildings outside of high hazard zones (flood, surge)	+	(Rubinoff & Courtney, 2007)	Brisbane City council
	Commercial buildings constructed after 1981	+	(Cutter et al., 2010)	NEXIS
	Industrial buildings constructed after 1981	+	(Cutter et al., 2010)	NEXIS
	Industrial buildings structural value	-	(Mayunga, 2009)	NEXIS
	Commercial buildings structural value	-	(Mayunga, 2009)	NEXIS
Economic capacity for response and recovery	Economic and livelihood stability			
	percent home ownership	+	(Cutter et al., 2010)	Census 2011
	percent employed population	+	(Cutter et al., 2010; Norris et al., 2008); UNDESA 2007	Census 2011
	Median household income	+	(Rose, 2007)	Census 2011
	Percent female labour force participation	+	(Cutter et al., 2010)UNDEASA 2007	Census 2011
	Median value of owner-occupied housing units	+	(Mayunga, 2009)	RPA
	Resources equity			
	Financial and insurance services per 10,000	+	Queste and Lauwe 2006	Census 2011
	Healthcare and social assistance services per 10,000	+	Greiving 2006, Cutter et al.2010	Census 2011
	Economic resources (SEIFA)	+		ABS
	Diversity			
	Percent of population not employed in primary industries	+	(Cutter et al., 2010)	Census2011
	Retail centres per 10,000 population	+	(Rubinoff & Courtney, 2007)	URP GIS data layers
	Ratio of large to small businesses	+	(Cutter et al., 2003)	--

5.3.3. Physical Indicators

The physical component is the least studied dimension of disaster resilience in terms of resilience composite indicators. Based on the common definition of resilience, physical resilience can be loosely defined as the capability of the built environment to absorb the adverse impacts of the shock on community, maintain its major structures and function and restore the affected structures quickly in order for the community to bounce back to its previous level of function (Mayunga, 2007). Existing infrastructure resilience models which take an engineering based approach to modelling resilience are not suitable for defining the physical component variables in a comprehensive resilience model. As an overall assessment of the buildings (residential/ commercial/ industrial/ public), lifelines (transport, power, water and communication), infrastructure (roads, bridges, dams and levees), and land and building regulations, land use planning and also critical facilities, is needed.

As previously discussed in Chapter 2, four of the resilience attributes discussed are more relevant to physical resilience in terms of articulating properties of the resilient built environment. These attributes, along with other resilience principles extracted from urban planning literature, are used to define the physical resilience metrics: 1) robustness in the built environment determines the risk avoidance measures which mainly represent the exposure. Robustness also represents the measures on continuance of providing services defined by the sensitivity of built environment elements; 2) redundancy characterizes measures for duplicating systems, equipment and supplies which assist the system in absorbing the shock and minimize the adverse impacts on the system. Temporary sheltering capacity, evacuation capacity and diversity variables will be covered by the metrics of this component; 3) resourcefulness and 4) rapidity are the properties which help the community to recover quickly. In addition, the availability of resources, such as materials and skills which represent reconstruction capacity, and also fire, SES and police stations that represent the response capacity, will accelerate recovery.

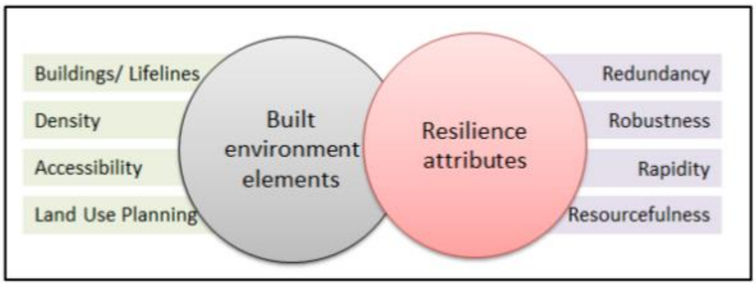


Figure 5.6. Conceptual framework of built environment resilience

So, in relation to physical resilience, the disaster impact on the built environment and the physical capacity of urban systems to respond to disasters can be best measured using the following indicators:

Table 5.4. Indicators identified for the physical dimension of disaster resilience

Component	Indicators	Effect direction	Justification	Data source
Physical impact	Exposure			
	Built up area in flood hazard areas	-	(Geis & Kutzmark, 1995)	BCC
	% Public services in flood hazard areas	-	(Geis & Kutzmark, 1995)	NEXIS
	% services in flood area (recreation and culture, commercial facilities, public services, defence facilities, research facilities)	-	(Chang and Shinozuka, 2004)	URP GIS data
	Sensitivity			
	% Building constructed after 1981	+	(Mayunga, 2009; Renschler et al., 2010)	NEXIS
	% Not single family detached houses	+	(Renschler et al., 2010; Rubinoff & Courtney, 2007)	NEXIS
Physical capacity to respond and recover	Medical capacity			
	# Ambulance services per 10,000	+	(Mayunga, 2009)	Census 2011
	# Hospitals per 10,000	+		QLD data
	Temporary sheltering capacity			
	# Schools per 10,000	+	(Chang & Shinozuka, 2004)	Census 2011
	% Recreational land per 10,000	+	(Cutter et al., 2010)	Census 2011
	% Education facilities per 10,000	+	(Cutter et al., 2010)	Census 2011
	# Sports facilities per 10,000			Census 2011
	# Caravan parks and camp areas per 10,000			Census 2011
	# Places of worship per 10,000			Census 2011
	Emergency response capacity			
	Police stations per 10,000	+	(Rubinoff & Courtney, 2007)	DCS
	Fire stations per 10,000	+		
	SES stations per 10,000	+		
	# Nursing homes per 10,000	+		
	% Services land use per 10,000	+		
	Communication capacity			
	Occupied housing units with internet connection	+	(Cutter et al., 2010)	Census 2011
	Transportation capacity			
	% Units with motor vehicle access	+	(Cutter et al., 2010)	NEXIS
	% Occupied housing units with a vehicle available	+	Mayunga,2011	Census 2011
	Access and evacuation potential			
	Intersection density per 10,000	+	Ewing and Cervero, 2010	URP GIS layers
	Principal arterial km	+	Cutter et al. 2010; Bruneau and Tierney 2007	URP GIS layers
	Diversity and redundancy			
	Dwelling density	+	(Alessa et al., 2009; Allan & Bryant, 2014; Berke & Campanella, 2006; March et al., 2011; Salat et al., 2010b)	Census 2011
	Land use mix	+		URP GIS layers
	Building type diversity (Simpson diversity index)	+		NEXIS

5.3.4. Environmental Resilience

The environmental components of resilience include measures of risk and exposure, existence of protective resources that safeguard communities against environmental threats, and also hazard event frequency (Gunderson, 2010; Holling, 2001).

Table 5.5 shows the variables selected for environmental resilience measurement. The risk and exposure subcomponent is represented by the percentage of land area which is not in a flood zone, the percentage of land area not in a sea level rise area, the percentage of residential land not in a flood risk area, and the length of the neighbourhood adjacent to the river. Hazard protection resources are defined by the percentage of land that is marsh, wetland, swamp and mangrove, the percentage of land area that is non-developed open space and the percentage of land area that is comprised of impervious surfaces. Measures of hazard event frequency are also linked with disaster resilience, since communities could become adapted to frequent disasters through mechanisms of learning from experience and selective pressure (Gunderson, 2010).

Table 5.5. Indicators identified for environment dimension of disaster resilience

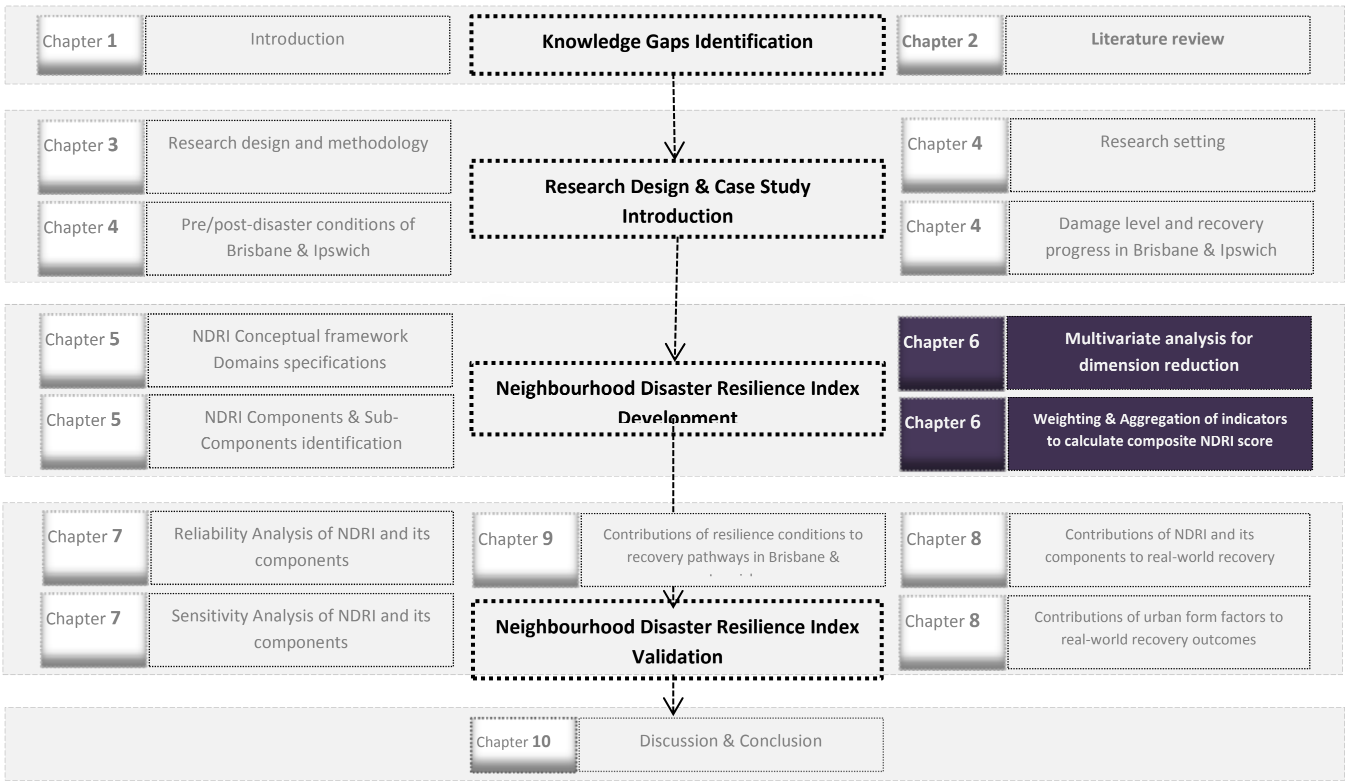
Component	Indicators	Effect direction	Justification	Source
Impact	Risk and Exposure			
	% land area not in a flood zone (100 &500 years)	+	(Cutter et al., 2010)	QLD Spatial database
	% Residential land not in flood risk area	+	(Cutter et al., 2010) (Geis & Kutzmark, 1995)	QLD Spatial database Brisbane City Council datasets
	Riverside length proximity	−		
Capacity to response & recovery	Protection resources			
	% land area that is a wetland, swamp, marsh, mangrove, sand dune, or natural barrier	+	(Adger et al., 2005; Geis & Kutzmark, 1995)	QLD Spatial database
	% area that is developed open space			
	% land area that does not contain impervious surfaces			
	Disaster frequency			
	% flooded in all three last flood events/flooded in 2011	+	Geis and Kutzmark, 1995)	GeoScience Australia spatial database

5.4. Summary

In this chapter, the theoretical framework for index development and its specifications are presented. Later, the indicators of resilience are identified using cross-classification. Two equally important criteria were considered in order for a variable to be considered appropriate and to be collected. First, it was essential that variables were justified based on the literature on the variable's relevance to resilience. The second criterion was that variables must be meaningful at the scale of this study, the neighbourhood level. Out of the 93 variables on the wish list, 76 of them are deemed fit to measure the resilience phenomena based on the two conditions mentioned above, and are included in further analysis.

Chapter 6
Index Development

Refinement of Indicators and Composite Index Calculation



6. Index Development - Refinement of Indicators and Composite Index Calculation

6.1. Overview

In previous chapters, the disaster resilience indicators at a neighbourhood level were extracted from the literature. In order to develop a reliable measure, dimension reduction techniques were utilised to reduce the dimensionality of the high dimensional datasets and to address the problem of high correlation among some of the selected variables. Later, three further steps were conducted to calculate the composite indicators and the overall score of disaster resilience for each neighbourhood. This chapter seeks to examine these questions using the following methodology:

Research Questions

- What set of variables provides the best parsimonious indicator set of disaster resilience at the neighbourhood level?
- How can these indicators be merged into an overall resilience composite index?

Methodology

To address the first question a series of multivariate analysis are conducted including principle component analysis and multidimensional scaling methods. Three further steps are conducted to calculate the overall Neighbourhood Disaster Resilience Index (NDRI) and the sub-components scores (including Neighbourhood Physical Resilience Index (NPhRI), Neighbourhood Economic Resilience Index (NEcRI), Neighbourhood Environment Resilience Index (NEnRI) and Neighbourhood Social Resilience Index (NSoRI)). These steps consist of scale adjustment and normalisations, weighting and aggregation (Figure 6.1).

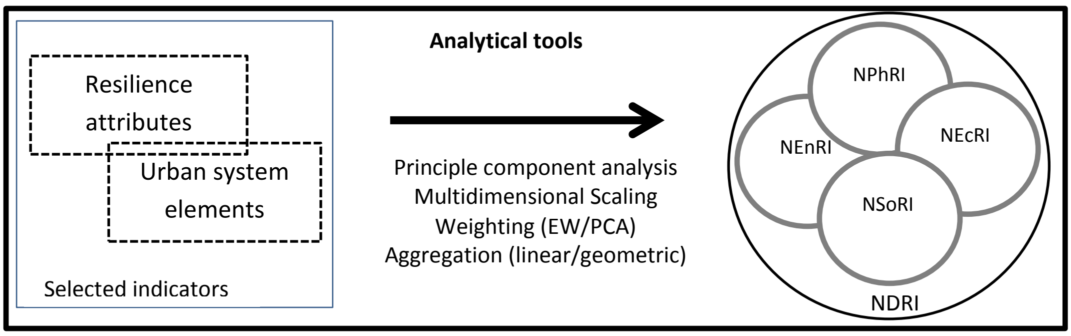


Figure 6.1. Multivariate meta-analysis diagram

6.2. Multivariate Analysis Procedure for Variable Selection

As described in Chapter 3, in this chapter multivariate analysis is conducted to check the underlying structure of the data along with the dimensions; and also to identify the group of indicators that are statistically similar. In this study, the factor analysis is not deemed suitable for dimension reduction purposes, as initial examination of the variables shows some violations of factor analysis assumptions. The analytical tools utilised in this chapter are principle component analysis (PCA) and multi-dimensional scaling analysis (MDSA) as non-parametric methods which do not need to meet any assumptions to analyse the data structure.

These analyses support the refinement of the selected variables by dropping the metrics which cross-loads on more than one factor and also validate the developed index by demonstrating the loading of each indicator on each component. They also facilitate the subsequent methodological choices for weighting and aggregation.

6.2.1. Principal Component Analysis (PCA)

Principal components analysis is a variable-reduction method which reduces a larger set of variables into a smaller set of 'artificial' variables that accounts for most of the variance in the original variables (Jolliffe, 2002). The main application of PCA is the analysis of multiple indicators, measurement and validation of complex constructs, index and scale construction and data reduction.

In this research, principle component analysis has been conducted to redefine the data using the best linear combination of the items, in order to reduce the noise and also to show the relationships in the dataset more clearly. The correlation between the principle components is negatively associated with PCA's strength, since lack of correlation demonstrations that these components are representing different statistical dimensions. The assumptions of this method are the linearity between variables and that it has no outliers. The principle components analysis assists in removing the unrelated variables. It allows the clustering together of the variables which all load on the same component. Principal components analysis also allows the reduction of a number of correlated variables into a single artificial variable called a principal component. PCA also removes the multi-linearity by reducing the highly correlated variables into principle components that can be used to generate a component score which can be used in lieu of the original variables.

The procedure involved in conducting PCA (Nardo et al., 2005):

1. Check the assumptions (sufficient number of cases/no bias in selecting individual indicators/no outliers/assumption of interval data/linearity/multivariate normality/underlying dimensions/strong inter-correlations).
2. In the inter-item correlations matrix, check whether all variables have at least one correlation above r=0.3.
3. Check the sampling adequacy by one of the tests below:

   (a) The Kaiser-Meyer-Olkin (KMO) for the overall data set. The KMO measure is used as an index to determine whether there are linear relationships between the variables and thus whether it is appropriate to run a principal component analysis on the dataset. Its value can range from 0 to 1, with values above 0.6 suggested as a minimum requirement for sampling adequacy, but values above 0.8 considered good and indicative of principal components analysis being useful.

   (b) The KMO measure for each individual variable.

   (c) Bartlett's test of sphericity. These are all discussed in the following sections. Bartlett's test of sphericity examines the null hypothesis that the correlation matrix is an identity matrix. Effectively, it is saying that there are no correlations between any of the variables. As such, the idea is to reject the null hypothesis by checking whether Bartlett's test of sphericity is statistically significant ($p < .05$) or not.
4. Check the communality (the proportion of each variable's variance that is accounted for by the principal components analysis). We expect that, as all the components are not accounted for, the communalities will be less than one.
5. Choose the criteria for components to retain. Now that all the principal components are extracted, it is necessary to determine how many components to retain for rotation and interpretation. Although there are some statistical considerations in deciding this number, some subjective judgements are also needed. With principal components analysis there is not one objectively correct answer; the correct number of components to retain is something to decide based on four major criteria. These are the eigenvalue-one criterion, the proportion of total variance accounted for, the scree plot test, and the interpretability criterion.
6. Report the principle components and component based scores. A component-based score is a composite score that is simply a summation of the scores on all of the variables that loaded strongly on a particular component. The major difference between component-based scores and component scores is that the original variables are not multiplied by optimal

weights in a component-based score. As such, this often results in component-based scores that are not orthogonal.

6.2.2. Multidimensional Scaling Method

The multi-dimensional scaling method is conducted as a second multivariate analysis to assure that the analysis is comprehensive enough and does not depend on a single method. Multi-dimensional scaling is a technique which models and represents similarity coefficients within the variable set based on the distance in multidimensional space (Cox & Cox, 2000). The multidimensional Euclidean plane can be thought of as maps of points in which the closer points may represent the underlying phenomenon.

Normally, a multi-dimensional scaling procedure needs five steps to be conducted, as below:

1. Computing the Euclidean distance matrix for all variables in t dimensional space. Since the distance from variable I to variable j (dij) is equal to the distance from variable j to variable I (dji), the distance matrix is symmetric and only half of the matrix is needed to be considered for analysis.

2. Depending on the MDS method selected, a linear, polynomial, or monotonic regression of dij on input distance between I and j should be employed. The results will be mapped.

3. For testing the results for validity and reliability a Kruskal STRESS test (Kruskal & Wish, 1978) is carried out to as a goodness of fit statistic based on the differences between the actual distances and their predicted values. STRESS measure is carried out, as below:

$$STRESS = \sqrt{\frac{\sum(d_{ij} - \hat{d}_{ij})^2}{\sum d_{ij}^2}}$$

In which dij represents the predicted distance based on the MDS model and depends on the number of dimensions kept and the algorithm used in MDS. From the equation above, MDS fits the best with STRESS values near zero. Kruskal (1964) offers the table below as an advice about STRESS value:

Table 6.1. Goodness of fit based on STRESS value (Kruskal, 1964)

STRESS	Goodness-of-fit
0.200	poor
0.100	fair
0.050	good
0.025	excellent
0.000	perfect

4. Steps two and three are repeated in such a way that STRESS cannot be further reduced. The outcome is a representation of n objects in t dimensions that are mapped as points on a two dimensional surface to show how objects are related.

6.2.3. Results of Dimension Reduction Analyses

6.2.3.1. Social Component

Social resilience indicators (21 variables) for 253 neighbourhoods in Brisbane and Ipswich have been introduced into a principle component analysis using the dimension reduction function in SPSS. To see whether PCA is appropriate for analysing this data set, a correlation matrix has been investigated and showed that all variables have at least one correlation coefficient greater than 0.3. The overall KMO is 0.74 with individual KMO measures all greater than 0.7, which according to the Kaiser (1974) scale, is equivalent to moderate adequacy. On the other hand, Bartlett's test of sphericity is statistically significant ($p < 0.0005$), indicating that the data has the potential for factorising. Six components are identified by PCA on the selected social resilience indicators with eigenvalues greater than one, which explain 28.46%, 20.50%, 10.45%, 7.72%, 5.48% and 4.73% of the total variance, respectively. Visual inspection of the scree plot and also interpretability criterion suggest that five components should be retained. The five-component solution explains 72.61% of the total variance. Moreover, a varimax orthogonal rotation has been utilised to aid interpretability, as the rotated solution showed a more balanced structure. The five components could be interpreted in consistency with the social resilience attributes found in the literature, with strong loadings of place attachment variables on component 1, not vulnerable population items on component 2, community participation items on component 3, human capital on component 4, and access to resources items on component 5. Component loadings and communalities of the rotated solution are presented in Table 6.2.

To ensure that from the results of PCA, the social resilience indicators were entered into the multidimensional scaling analysis using the program ALSCAL. STRESS which is the goodness of fit measure in this analysis is illustrated in the table below. A five dimensional representation of the data seems to be the optimal dimensionality, based on the common practices iterated within the multivariate statistics. In practice, an optimal MDS solution can be found in three or less dimensions, and small values of STRESS (close to 0) are desirable. Kruskal and Wish (1978) indicate that a reduction in the number of dimensions so that STRESS exceeds 0.100, or an increase in the number of dimensions when STRESS is already less than 0.050 is questionable.

Table 6.2. Rotated structure matrix for PCA with varimax rotation of social resilience indicators

variables	Rotated Component Coefficient					
	1 Place attachment	2 Not vulnerable population	3 Participation	4 Human capital	5 Access to resources	Communalities
% residents moved >5 years ago	**.840**	.133	-.109	-.140	-.104	.767
% home owner	**.826**	-.415	-.028	.168	-.054	.890
% migrants arrived before 2009	**.716**	-.152	.199	-.385	.472	.871
% pop not need assistance	.267	**.820**	-.103	-.064	.107	.755
% pop not rent public housing	-.139	**.657**	-.141	-.130	-.090	.560
% age between 5 and 65	.587	**.658**	-.019	.115	.007	.773
% single parent family	.079	**.571**	-.608	-.193	-.128	.822
% volunteers	.094	.066	**.856**	.115	.092	.824
% unpaid voluntary work	.214	-.456	**.304**	.394	-.626	.857
human capital index (SEIFA)	.061	-.012	.375	**.842**	-.38	.894
% population with sufficient English	-.101	.023	-.242	-.599	**.763**	.776
% education >year 8	-.029	-.036	-.028	.146	**.242**	.393

Extraction method: Principal component analysis.
Rotation method: Varimax with Kaiser normalization.
a. Rotation converged in 8 iterations.

To interpret the multi-dimensional scaling output, this study looks for groups of objects in terms of their distance. Table 6.2 shows that the first factor largely reflects the place attachment. This cluster includes the percentage of home owners and the percentage of residents living in the same address as they were 5 years ago. The second cluster has been shaped around variables representing the population which is not vulnerable, such as the percentage of population not needing assistance, the percentage of renters not renting public housing, the percentage of population age >5 and <65 and the percentage of families who are not single parent families. Along the third dimension, community participation metrics can be seen. These metrics include the percentage of the population who volunteered the percentage of the population who are doing unpaid voluntary work and the percentage of the population who are giving unpaid assistance. As evident in the component plot in rotated space, human capital metrics are clustered together. It includes the percentage of manufacturing services, the percentage of healthcare services, the percentage of construction services, the percentage of transportation services, the percentage of financial and insurance services, the percentage of accommodation and food services. In the fifth dimension, three variables are coupled strongly, including the percentage of the population who do not speak English well, the percentage of the population with a school education lower than year 8, and the percentage of the population who are immigrants who arrived after 2009.

Table 6.3. Multidimensional scaling goodness of fit for social component

Dimension/Iteration	S-stress	Stress Improvement	R-Square
1	.088	----	.73
2	.067	.022	.84
3	.048	.019	.920
4	.032	.016	.948
5	.029	.003	.965

Not vulnerable population - This sub-component of social resilience consists of 4 variables: the percentage of population age >5 and <65, the percentage of families who are not single parents, the percentage of the population who do not need assistance, the percentage of the population who not rent public housing. In both PCA and MDSA, they show consistency in their effect direction and also in their inter-item correlation.

Place Attachment - Consists of the percentage of home ownership, the percentage of migrants who arrived before 2009 and the percentage of the population who had the same address 5 years ago.

Participation - This subcomponent includes the variables which show the level of participation in neighbourhoods. Following PCA, the percentage of volunteers, and the percentage of unpaid volunteer workers showed high commonalities, but the percentage of people doing unpaid assistance work did not have the same effect direction and therefore was omitted.

Access to resources - This component includes the percentage of the population who have a sufficient knowledge of English, and the percentage of the population who have an education higher than 8th grade. Based on the PCA result, they did not show the same effect direction and therefore the education variable was moved to the human capital subcomponent.

Human Capital - This subcomponent shows the level of human resources available within the neighbourhood and included the percentage of the population who are healthcare employees, the percentage of construction employees, the percentage of electricity, water and waste management employees, the percentage of financial institutes employees, the percentage of manufacturing employees, the percentage of transportation employees, and the SEIFA human capital index. The PCA showed very high loading of the human capital index on this sub-component compared to the other indicators, and therefore only the human capital index is kept in the index as a parsimonious indicator for the human capital sub-component.

6.2.3.2. Economic Component

Principle component analysis is conducted on 17 indicators selected for economic resilience on 253 neighbourhoods of Brisbane and Ipswich. To assess the suitability of PCA for this analysis, the correlation matrix was inspected and it showed that all variables have at least one correlation coefficient greater than 0.3. The Kaiser-Meyer-Olkin (KMO) measure was 0.793 and all individual KMO measures were greater than 0.7, which is meritorious according to Hair et al. (2006). Bartlett's test of sphericity was statistically significant ($p < .0005$); this confirms that the data can be factorized. Conducting principle component analysis revealed six factors that had eigenvalues greater than one, which explained 32.7%, 14.5%, 8.72%, 7.9%, 6.64% and 5.92% of the total variance, respectively. By checking the other criteria for deciding the number of components, visual inspections of the scree plot showed that four components in this dataset could be retained (Cattell, 1966). Moreover, this four component solution meets the interpretability criterion.

The solution which retained four components explains 63.84% of the total variance. A varimax orthogonal rotation was employed to aid the interpretability. This rotation exhibited a simple structure which is consistent with the resilience attributes in economic system. This dataset shows a strong loading of economic resources and stability items on component 1, economic equity on component 2, exposure and sensitivity on component 3, and economic diversity on component 4. Component loadings and communalities of the rotated solution are presented in Table 6.4 below.

Table 6.4. Rotated structure matrix for PCA with varimax rotation of economic resilience indicators

variables	Rotated Component Coefficient				
	Economic Stability	Asset Exposure	Economic Diversity	Resource Equity	Communalities
% employed population	**.875**	-.096	.007	.126	.790
Median household Income	**.873**	-.204	.016	.257	.870
% female labour force participation	**.868**	-.039	-.054	.111	.771
Median house value	**.197**	.289	.320	.133	.470
% financial & insurance services	.445	.224	.152	**-.370**	.657
% healthcare & social assistance services	.392	.046	.053	**-.422**	.661
Economic resources (SEIFA)	.097	.293	-.070	**.387**	.793
% commercial buildings outside of flood zone	.038	**.509**	-.185	.359	.423
% commercial buildings built after 1981	-.014	**.324**	-.831	-.153	.715
% population employed in primary industries	.085	.000	**.717**	-.397	.679
# retail centres per 10,000	-.056	.062	**.239**	-.438	.298

Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization.
a. Rotation converged in 6 iterations.
Note. Major loadings for each item are in bold

Multi-dimensional scaling has been used as a second method of dimension reduction. It revealed four strong associations based on the distance between variables in Euclidean space. In practice, an optimal MDS solution has lower levels of STRESS (close to 0). Kruskal and Wish (1978) specify that reducing the number of dimensions so that STRESS might exceed 0.100, or increasing the number of dimensions so that that the STRESS goes down to less than 0.050 is problematic. For that reason the addition of a fifth dimension has no justification for further consideration in this analysis. The output of MDS in Figure 2 along the first dimension shows that the median income, percentage of population employed and the percentage of the female labour force participation, making a cluster of similar dimensions in theory in terms of their distances. These variables directly relate to the livelihood and economic stability of communities.

Another cluster can be seen around the second dimension and includes variables such as the percentage of commercial addresses per 10,000 population (PerComAddr10000), the percentage of commercial buildings built before 1981 (PerComBuiPre1981), commercial land ratio and property value. This cluster shows the extent to which the economic assets are exposed and sensitive to disasters. The cluster along the third dimension consists of the percentage of the population not employed in primary industries and the percentage of retail centres per 10,000 head of population (PerRetailCentres10000). This component represents economic diversity.

The fourth dimension includes the percentage of home owners, the percentage of healthcare and social assistance services, the percentage of financial and insurance services and the economic resources index (SEIFA), which explains the resources equity.

The ratio of industrial land and the percentage of industrial buildings built prior to 1981 have been identified by the MDS procedure to be the only poorly positioned. This might be due to the fact that they are the only variable measuring exposure of industrial land use within the component's set variable set.

Table 6.5. Multidimensional scaling goodness of fit for economic component

Dimension/Iteration	S-STRESS	STRESS Improvement	R-Square
1	.097	---	.668
2	.085	.012	.802
3	.076	.009	.886
4	.059	.007	.951

Asset exposure - This sub-component includes property values (content and structure), commercial land ratio, industrial land ratio, commercial addresses per 10,000 and commercial buildings built prior to 1981.These variables showed high loadings on the third component in PCA except for property's values, which is omitted from this sub-component. This sub-component theoretically has a negative correlation with disaster resilience. However, as this condition is not necessary for housing recovery, it will not be considered in the validity assessment and qualitative comparative analysis sections.

Economic and livelihood stability - This sub-component includes median family income, the percentage of employed population, the percentage of female labour force participation and the SEIFA economic resources indicator. They have the highest loadings on the economic component with a positive effect on disaster resilience.

Resource equity – The percentage of financial and insurance employees, the percentage of healthcare and social assistance services and the percentage of home owners are clustered in the second component in the economic PCA.

Economic diversity - The percentage of the population employed in non-primary industries and the number of shopping centres per 10,000 head of population were grouped to measure economic diversity. Economic diversity relates to the ability of an economy to keep an acceptable level of function by guaranteeing a considerable inflow of capital for redevelopment and reconstruction. It also reduces the boom and bust nature of a single sector economy in an extreme disaster (Cutter et al., 2010).

6.2.3.3. Physical Component:

Principle component analysis of the physical resilience subcomponent has shown six distinct dimensions (Table 6.6). Varimax rotation has been used in PCA to enhance interpretability by maximising the loading of individual indicators in individual factors. These factor loadings shown in the table below will be used later to construct weights for the NDRI and NPhRI composite indicators.

The percentage of educational facilities per 10,000 head of population, the number of caravan parks and camping areas per 10,000 and the number of nursing homes per 10,000 did not have significant loadings on any component that could be interpreted. Thus, these variables were removed from further analysis to find a clearer structure in PCA procedure.

The first identified component in principle component analysis represents the urban form variables. It includes dwelling density, building type diversity, percentage of families who are not single parent families, detached houses and land use mix with loading values of respectively 0.915, 0.895, 0.893 and 0.328. The second component comprises variables representing temporary shelter capacity, including the number of schools per 10,000 people, percentage of recreational land per 10,000, number of sport facilities per 10,000 and number of places of worship per 10,000, which have loadings of 0.375, 0.481, 0.389, 0.621 and 0.476 on this component respectively.

Medical land use areas per 10,000 people, number of hospitals per 10,000 and healthcare employees per 10,000 create a cluster which shows the medical capacity of the neighbourhood. Although the first two variables have higher loading values (0.933 and 0.897) on this component compared to the last one that has loading value of 0.355, theoretically it is better that they are kept in the same component. The percentage of units with a vehicle, the percentage of units with vehicle access, principle roads per 10,000 and road intersections per 10,000 were clustered around the fourth component, the accessibility with loading values of 0.204, 0.432, 0.306 and 0.736, respectively.

The fifth component includes number of fire stations per 10,000 head of population, number of police stations per 10,000 and the percentage of services land use with 0.895, 0.894 and 0.457 loading values, respectively. Although SES centres show a low loading value of 0.355 on this factor and are less tightly coupled with other variables in terms of their distance, keeping SES centres in this component helps to interpret this component as the emergency response capacity of the neighbourhood.

Lastly exposure variables, including the percentage of non-built-up areas in a flood zone, percentage of public services in a flood zone and percentage of services in a flood zone are clustered together in the sixth component, with loading values of 0.488, 0.437 and 0.328.

Table 6.6. Rotated structure matrix for PCA with varimax rotation of physical resilience indicators

Variables	Rotated Component Coefficient						
	1 Urban form	2 Sheltering capacity	3 Medical capacity	4 access ibility	5 Response capacity	6 Impact	Communalities
dwelling density	**.915**	-.140	-.090	-.203	-.102	-.081	.924
building type diversity	**.895**	-.153	-.088	-.237	-.123	-.029	.904
% non single family detached houses	**.893**	-.168	-.095	-.235	-.124	-.127	.921
LUM5	**.328**	-.213	-.017	.638	.123	-.077	.526
%education land use per10,000	-.081	**.074**	.739	-.035	-.023	-.098	.564
# schools per10000	-.095	**.375**	-.013	.601	-.093	-.125	.399
% recreation land per 10,000	.074	**.431**	.076	.014	.204	.037	.743
% sport facilities per 10,000	.398	**.389**	.038	.343	.034	.134	.830
% caravan parks per10,000	.054	**.621**	.352	.012	.006	.054	.487
% places of worship per 10,000	.176	**.476**	.243	.055	.128	.320	.693
% medical land use area 10,000	.048	-.025	**.933**	.067	-.024	.033	.879
# hospitals per 10,000	.126	.000	**.897**	.113	.023	-.020	.833
# ambulance services per 10,000	.103	.002	**.432**	.210	.022	.102	.647
% occupied unit with vehicle	-.676	-.147	-.170	**.204**	-.161	.108	.732
% units with motor vehicle access	-.247	.342	.032	**.432**	.347	.076	.658
principle roads per 10,000	-.273	.360	.060	**.306**	.174	.005	.545
# road intersections per10,000	-.356	.460	.010	**.736**	.384	.081	.708
# fire stations per 10,000	-.033	-.042	-.035	-.005	**.895**	-.007	.806
# police stations per 10,000	.035	-.057	.003	-.027	**.894**	-.094	.813
# SES per 10,000	-.15	.438	-.007	-.163	**.312**	.015	.571
% services land use per 10,000	.043	.32	-.065	.076	**.457**	.034	.573
% building age post1981	.516	.118	-.022	.360	.096	**.488**	.436
% non built-up in flood area	.052	.371	.287	.021	.201	**.437**	.530
% public services in flood area (-)	.031	.012	.143	.150	-.031	**.328**	.632

Extraction method: principal component analysis.
Rotation method: Varimax with Kaiser normalization.

The output of the multi-dimensional scaling analysis for physical component variables is shown in Table 6.7. The MDS approach revealed similar associations between variables with six distinct dimensions.

Table 6.7. Multidimensional scaling goodness of fit for physical component

Component	STRESS	STRESS Improvement	R-Square
1	.095		
2	.075	.020	.608
3	.066	.009	.793
4	.061	.005	.888
5	.059	.002	.930
6	.058	.001	.956

Physical Exposure- This subcomponent consists of the percentage of non-built up areas and the percentage of public services land use in flood risk areas.

Shelter capacity - This includes the number of schools per 10,000 head of population, the percentage of recreation land per 10,000 people, the number of sports facilities per 10,000, and the number of places of worship per 10,000 people. The percentage of educational land use per 10,000 had a very low loading on this component, so this variable was omitted from the shelter subcomponent.

Medical capacity - Consists of number of ambulances per 10,000, number of hospitals per 10,000 and percentage of medical land use for 10,000 people, which all are loading onto the third component.

Response capacity - This subcomponent includes variables which measure the capacity to respond in the event of a disaster. It includes the number of fire stations per 10,000, the number of police stations per 10,000, the number of SES stations and also the percentage of land services per 10,000 people.

Transportation capacity - The variables in this group measure the transportation capacity and accessibility of neighbourhoods including the percentage of occupied dwelling with vehicles, road intersections per 10,000 and the percentage of units with motor vehicle access.

Redundancy and diversity - This subcomponent consists of urban form variables, including land use mix, building type diversity, dwelling density and the percentage of detached houses with families which are not single parent families. They show high loadings on the first component and have a positive effect on disaster resilience.

6.2.3.4. *Environmental Component:*

Eleven indicators of the environmental component have been entered in a principle component analysis on 154 neighbourhoods of Brisbane and Ipswich. PCA assumptions were checked first by a correlation matrix which showed that at least one correlation coefficient of each variable is greater than 0.3. On the other hand, the Kaiser-Meyer-Olkin (KMO) measure was 0.712 and all individual KMO measures were all greater than 0.7, which according to Kaiser (1974), means that they are all acceptable. Bartlett's test of sphericity was statistically significant ($p < .0001$). Thus the data of these eleven indicators can be factorised. Three components were identified by conducting PCA which have eigenvalues greater than one – and this explains 41%, 16% and 11% of the total variance, respectively. Visual inspections of the scree plot showed that three components in this dataset can be reserved, although the third component misses the interpretability criterion. A varimax orthogonal rotation was employed to aid the interpretability. This rotation exhibited a simple structure which is consistent with the resilience attributes in an environmental system. The solution retaining four components explains 70% of the total variance. This dataset showed a strong loading of risk and exposure variables on component 1, protection resources items on component 2 and hazard frequency items on component 3. Component loadings and communalities of the rotated solution are presented in Table 6.8 below.

Table 6.8. Rotated structure matrix for PCA with varimax rotation of environmental resilience indicators

	Component		
	Hazard frequency	Protection resources	Risk and exposure
% developed open space	-.228	**.718**	.097
% pervious surface	-.058	**.655**	.440
% marsh wetland	-.183	**.660**	-.245
% land not in flood risk area	.373	.257	**.443**
% residential not in flood area	.378	.280	**.477**
River Km (-)	.182	-.650	**.286**

Extraction method: principal component analysis.

a. 3 components extracted.

a. Rotation converged in 6 iterations.

Note. Major loadings for each item are in bold

Table 6.9. Multi-dimensional scaling goodness of fit for economic component

Dimension/Iteration	S-STRESS	STRESS Improvement	R-Square
1	.032	---	.997
2	.025	.0066	.994
3	.024	.0009	.992

Risk and exposure - This subcomponent includes the percentage of land not in a flood risk area, the percentage of residential land not in a flood risk area, the length of the neighbourhood next to the river. The length of the neighbourhood next to the river was omitted in this case study, considering that the level of the neighbourhood (neighbourhoods next to the river with very high levels such as Kangaroo Point as opposed to the low level neighbourhoods next to the river such as Saint Lucia) could have inconsistent effects on the exposure subcomponent. The percentage of land not in a flood zone and the percentage of residential land not in a flood zone moderate the level of flood impacts on any neighbourhood, and in this way they could contribute to the resilience of the neighbourhood.

Protection resources - The percentage of developed open space, the percentage of pervious surface and the percentage of wetland/marsh land are grouped as protective resources which buffer neighbourhoods against environmental hazards and contribute to the disaster resilience of the neighbourhood.

Hazard frequency - Flood frequency could be associated with disaster resilience, as neighbourhoods may adjust to recurring floods by selective pressure mechanisms (Gunderson, 2010). These neighbourhoods will have had the experience of a previous flood and most probably anticipate future disasters by knowing when and where the flood might occur. This measure is defined by the ratio of the lands which have been affected by floods three times to land affected by the flood in 2011.

In this section, multivariate analysis (PCA and MDSA) have been conducted to check the underlying structure of the data along different dimensions and the sub-groups in these dimensions. The results of MVA on data set structure and the interpretation of the components and sub-components have been analysed and compared to the theoretical framework proposed in Chapter 4. Table 6.10 shows the refined set of variables after multi-variable analysis.

Table 6.10. Refined set of selected variables of disaster resilience

Variable		Analysis Abbreviation
Social		
Not vulnerable population		
1	% population aged not less than 5 or more than 65	POPAGE
2	% population not need assistance	POPASSIST
3	% renter renting public housing	NOTRENTPBLC
4	% non single parent family - family composition	NOTSINGPRNT
Place attachment		
5	% residents moved more than five years ago	RSDNTMVD5
6	% home owners' occupancy	OWNRS
7	% immigrants arrived before 2009	IMMIGPRE2009
Access to resources		
8	% education higher than year 8	EDCTN8
9	% population with sufficient English	ENGLSHSFFCNT
Participation		
10	voluntary work for an organization or group	VLNTWRK
11	unpaid assistance to a person with disability	UNPDASSIST
Human capital		
12	human capital - SEIFA	HMNCPTLSEIFA
Economic		
Sensitivity/ vulnerability		
1	% commercial buildings constructed post1981	BLTPST1981
2	% commercial buildings outside of flood risk area	BLDOUTFLD
Economic and livelihood stability		
3	% population employed	EMPLYD
4	median householdincome	FMLYINCM
5	% female labour force participation	FMLLBRFRC
6	median house value	MHSVLU
Resources equity		
7	financial and insurance services per 10,000	FNNCLINSRNC
8	healthcare and social assistance services per 10,000	HLTHCR
9	economic resources – SEIFA Index	ECNMCRSRCSSEIFA
Diversity		
10	% population not employed in primary industries	NOTEMPPRMINDUST
11	# retail centres per 10,000 population	RTLCNTRS
Physical		
Physical exposure		
1	non built up area in flood hazard areas	NONBLTUP
2	%services in flood area (recreation and culture, commercial facilities, public services, defence facilities, research facilities)	PBLCSRVCS
3	% building constructed after 1981	BLDNGPST1981
4	% not single family detached houses	NOTSNGLDETACH
Medical capacity		
5	# ambulance services per 10,000	AMBLNC
6	# hospitals per 10,000	HSPTLS
Temporary sheltering capacity		
7	# schools per 10,000	SCHOOL
8	% recreational land per 10,000	RECREATION
9	# education facilities per 10,000	EDTFCLT
10	# sport facilities per 10,000	SPRTSFCLTS
11	# placse of worship per 10,000	WRSHP

Emergency response capacity		
12	police stations per 10,000	POLICE
13	fire stations per 10,000	FIRE
14	SES stations per 10,000	SES
15	% services land use per 10,000	SRVCLND
Communication capacity		
16	Occupied housing units with internet connection	INTRNTACCSS
Transportation capacity		
17	% units with motor vehicle access	VHCLACCSS
18	% occupied housing units with a vehicle available	VHCLAVLBL
19	intersection density per 10,000	INTRSCTION
20	principal road	PRNCPLROAD
Urban form		
21	land use mix index	LUM
22	building type diversity	BTD
23	dwelling density	DWDNSTY
Environment		
Risk and exposure		
1	% land area in a flood zone (100 & 500 years) (-)	LNDNOTINFLOOD
2	% residential land in flood risk area (-)	RSDNTLNOTINFLOOD
3	riverside length km	RVRSDKM
Protection resources		
4	% land area that is a wetland, swamp, marsh or natural barrier	WTLNDMRSH
5	% land that is developed open space	DVLPDOPNSPC
6	% land area that does not contain impervious surfaces	IMPRVSLND
Disaster frequency		
7	% flooded 3 times to flooded in 2011	HZFRQNCY

6.3. Procedure of Composite Indicators Calculation

The Neighbourhood Disaster Resilience Index as a composite indicator is intended to measure the relative disaster resilience at neighbourhood level in the Australian context. As many authors advise (Tate, 2012), the rational for choices made in the process of index development is articulated precisely. Uncertainty and sensitivity analysis are used frequently during the index construction to check the robustness of the alternative methods at each stage of index development. However, the subjectivity and uncertainty at each step of index development is acknowledged.

Step 1: Scale Adjustment and Normalisation

The first step in calculating the composite indicator is to adjust the scale. In this study, the scale of indicators is adjusted by percentage or ratio per 10,000 head of population to avoid the small fractions of numbers after transformation (considering the value-ranges of indicators, the ratio per 10,000 is a reasonable scale). On the other hand, the selected indicators' data have different units as they are obtained from different sources. Therefore, to avoid adding apples and oranges and to be able to combine and compare indicators, they have been normalised to become unit-less measures. Normalisation also helps in avoiding the domination of extreme values and also to minimize the potential problems of data quality. There are different normalization methods in the literature including z-score, min-max, distance to reference (Briguglio et al., 2009). Each of these methods has its own advantages and disadvantages. For the purpose of this study a min-max method is used to standardize the selected set of indicators. The min-max is given by equation 5.1 (Freudenberg, 2003).

The reason for choosing this method is that it facilitates the calibration of data for qualitative comparative analysis (QCA) as its scaling factor is based on a range. The impact of outliers on the index due to this range-based scaling is controlled by excluding the outliers by kernel-based outlier detection and exclusion (Freudenberg, 2003).

Step 2: Weighting

To combine the selected indicators in a meaningful way and to develop a composite indicator, the weighting and aggregation system is carefully selected. According to Nardo et al. (2005) there are a number of weighting techniques, some derived from statistical models (parametric) and some derived from participatory methods (non-parametric). Statistical models for weighting generally include factor analysis, principle component analysis (PCA), unobserved components models (UCM), and participatory methods generally include the budget allocation process (BAP), analytic hierarchy process (AHP) and conjoint analysis (CA).

Statistical models for weighting account for the highest variation in the data set, using the smallest possible number of factors that reflect the underlying statistical dimensions of the dataset. This sort of weighting does not consider the theoretical importance of each variable, rather it interfers just for correction of overlapping information of the correlated variables. In this research, principle component analysis has been used as a parametric solution for weighting, assuming that there is some structure behind the variation of the included indicators. Hence the weights for these indicators are determined objectively by the covariation between them on each dimension of the structure. The use of factor score regression weights obtained from the PCA model minimizes measurement errors in the indicators contributing to each component, thus increasing the reliability and validity of the computed overall score.

Participatory methods are not considered in this study. However, as is the case for most of the composite indicators in the risk and vulnerability field (such as CDRI and URI), equal weighting is also utilised in this study due to the insufficient knowledge about the underlying relationships between indicators or how they correspond to the situation. An equal weighted component score is simply a summation of the scores on all the variables that loaded strongly on a particular component. The major difference between equal weighted component scores and PCA component scores is that the original variables are not multiplied by optimal weights.

Therefore, in this study, equal weighting and principle component analysis are chosen as weighting alternatives for calculation of the composite indicator. Here, the impact of weighting has not been over emphasized as it is tested for sensitivity and robustness in the next chapter.

PCA weighting results

In the common method of weighting using PCA, the first PC is always retained since it accounts for the largest amount of variability in the data. Then, the correlation coefficient between each indicator variable belonging to the particular sub-component and the first PC are calculated. The following formula is used to determine the weights:

W_{ij} = weight corresponds to j_{th} variable in i_{th} subset
r_{ij} = correlation coefficient between the first PC of i_{th} subset and j_{th} variable
i= 1, 2,.., m (number of subsets)
j= 1, 2,., n (number of variables in i_{th} subset)

In this study, the method introduced by Nicoletti et al. (2000) is utilised to weight the components of NDRI based on the explained variance in the data set. This method is somehow different from other typical methods in the literature using PCA to weight composite indices, since it does not consider only the first principle component to weight the index; rather it also considers the factor loadings of the consecutive extracted components. The benefit of this method is that a larger proportion of the variance in the data set is explained. The weights in this method are equal to the proportion of the explained variance in the data set. For example the weighting of the first intermediate composite index was 0.305 calculated as follows:

Physical PC 1 weight= (3.766/ (3.766+1.947+1.804+1.787+1.528+1.524)) = (3.766/12.356)= 0.305

The same formula is used to calculate the weights of other sub-components (Table 6.11). The consecutive sub-components accounts for less variability in the data set, decreasing from 5.71 to 1.07 in the social dimension, from 4.71 to 1 in the economic dimension, from 3.76 to 1.54 in the physical dimension and from 2.12 to 1.59 in the environment dimension.

Table 6.11. Principal components weights calculated based on explained variance

Principle Components	Explained variance	Component weight
Social Resilience		
PC1: not vulnerable population	5.719	(5.719/14.554)=0.393
PC2: place attachment	4.092	(4.092/14.554)=0.281
PC3: participation	2.084	(2.084/14.554)=0.143
PC4: access to resources	1.589	(1.589/14.554)=0.109
PC5: human capital	1.070	(1.070/14.554)=0.0735
		Economic Resilience
PC1: economic and livelihood stabilities	4.711	(4.711/7.574)=0.622
PC2: resource equity	1.860	(1.860/7.574)=0.245
PC3: economic diversity	1.003	(1.003/7.574)=0.13
		Physical Resilience
PC1: urban form/redundancy & diversity	3.766	(3.766/12.356)= 0.305
PC2: sheltering capacity	1.947	(1.947/12.356)=0.157
PC3: medical capacity	1.804	(1.804/12.356)=0.146
PC4: accessibility	1.787	(1.787/12.356)=0.145
PC5: response capacity	1.528	(1.528/12.356)=0.124
PC6: reconstruction capacity	1.524	(1.524/12.356)=0.123
		Environment Resilience
PC1: risk & exposure	2.118	(2.118/3.7.04)=0.571
PC2: protection resources	1.586	(1.586/3.704)=0.428

Step 3: Aggregation

Nardo (2005) suggests three general aggregation methods in developing composite indicators including additive, geometric and multi-criteria aggregation. In other words, the selected variables could be added up, multiplied or aggregated by non-linear methods. Each of these techniques has different assumptions and has particular consequences. Table 6.12 shows the relationship between aggregation and weighting methods in developing composite indicators. These combinations guarantee that information is not lost in the mathematical procedures.

Compensability is an important criterion in choosing the aggregation method. Aggregation methods with compensability allow a neighbourhood that has a good score on many indicators to have a better overall score compared to a neighbourhood that is better on a few indicators. In this regard, additive aggregation implies a full compensability while multi-criteria is a non-compensability method and the geometric aggregation is the intermediate solution. For example, in the additive aggregation method, two neighbourhoods with social, economic and physical resilience scores of 32, 2, 2 and 12, 12, 12 would have equal resilience scores, while as it is evident from their component scores, these two neighbourhoods have very different conditions which cannot be revealed in the composite score by this method.

Table 6.12. Well-matched weighting and aggregation methods

Weighting methods	Aggregation methods		
	Linear	**Geometric**	**Multi-criteria**
Equal weighting	Yes	Yes	Yes
Principle component	Yes	Yes	Yes
Benefit of doubt	Yes	No	No
Unobserved component models	Yes	No	No
Budget allocation	Yes	Yes	Yes
Analytic hierarchy process	Yes	Yes	No
Conjoint analysis	Yes	Yes	No

Considering that all variables inside the sub-components are latent variables, the compensability is allowed at this level of aggregation, and averaging is an appropriate method for calculating the sub-component scores. This method also reduces the influence of different number of indicators in each sub-component, which could put down the balance of the final composite indicator as the dimensions with more indicators would have implicitly higher weights in calculating the composite index (Nardo et al., 2005).

The overall scores for NDRI and each dimension are calculated using linear and geometric aggregation methods. In a benchmarking exercise, if the aggregation method is geometric, a neighbourhood has to enhance the resilience in dimensions with the lowest score in order to have the highest chance of improving its position in the ranking. On the other hand, when the aggregation method is linear, the neighbourhood has an interest in specialising along its most effective dimensions.

Linear aggregation is used to calculate the overall scores since this method is used by most of the related risk, vulnerability and resilience indices. However, the geometric aggregation method has also been used to overcome the drawbacks of the additive aggregation method, including its full compensability which allows poor performance of some indicators be compensated by adequately high scores of other indicators. The geometric aggregated score of NDRI is calculated based on this formula.

$$CI_c = \prod_{q=1}^{Q} X_{q.c}^{w_q}$$

The robustness and reliability of each composite indicator calculated using these different methods is analysed by sensitivity and reliability analysis in the next chapter.

6.4. Summary

In Chapter 5, a wish list of 93 indicators has been identified based on their measurability and relevance by reviewing the literature and deductive extraction of the indicators using the proposed framework. Seventy six of these variables have been within reach, and data were collected for further multivariate analysis. As the individual indicators were selected subjectively without considering the interrelationships between them, this could have resulted in misinforming composite indicators. Therefore, in this chapter the nested structure of the disaster resilience composite indicator has been examined using two separate multivariate analysis tools: principle component analysis and multi-dimensional scaling analysis. The results reveal some inconsistencies in the effect direction and loadings.

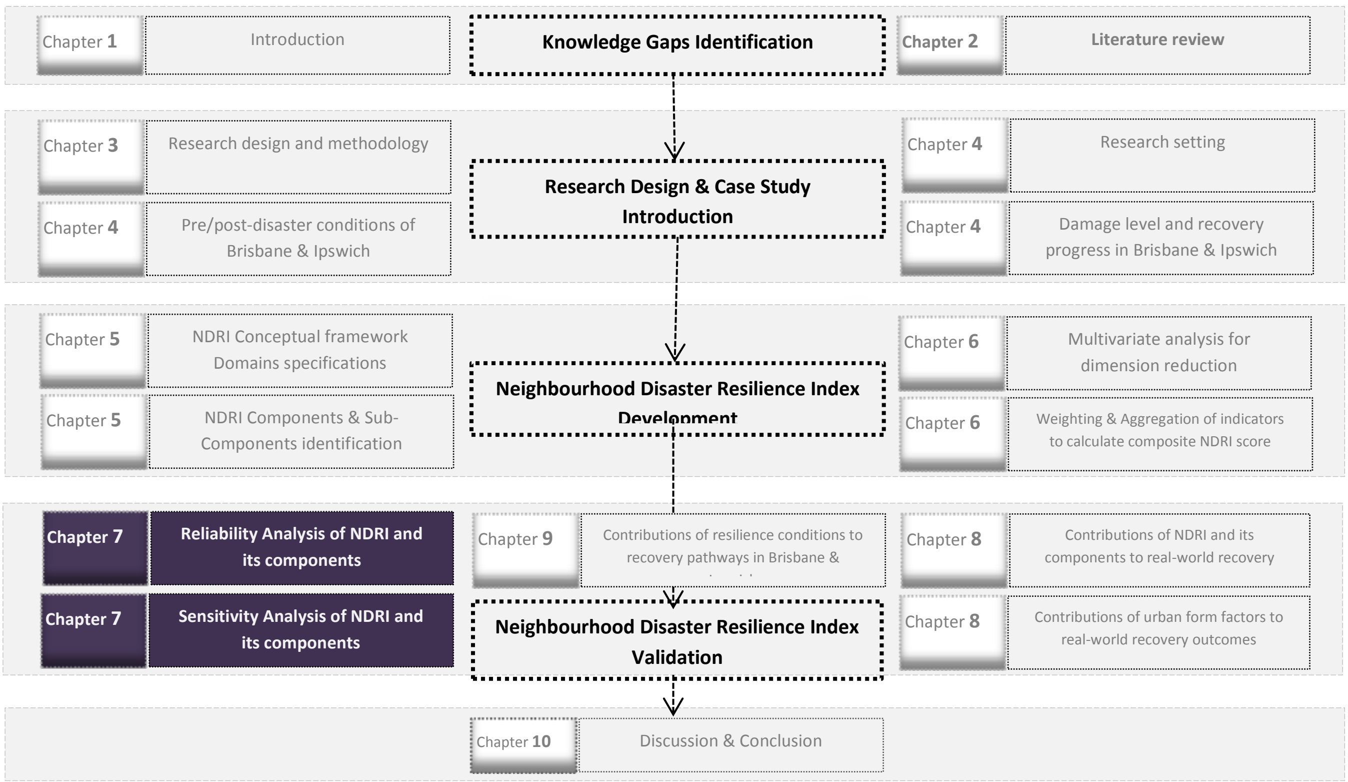
The underlying structure of the data show that some variables cannot be grouped with other variables, as was hypothesized in Chapter 5. First, correlation analysis has been applied to reduce the redundant variables from 76 to 65. Furthermore, principle component analysis (PCA) has been employed to redefine the data using the best linear combination of the items and reducing the number of the variables to a smaller set of 'artificial' variables that account for most of the variance in the original variables. Multi-dimensional scaling (MDS), on the other hand, has been used to identify the similarities and dissimilarities between indicators, and to assess the internal consistency of the data set based on the distances between variables in Euclidean space. As a result of PCA and MDS analyses, 12 variables have been excluded from further analysis. Table 6.12 shows the 56 variables considered as final set of variables in this research. These 53 variables provide the best parsimonious set of indicators for measuring resilience at the neighbourhood level. Moreover, principle component analysis has played a confirmatory role in identifying the sub-components of each component.

Each subcomponent of resilience is treated separately for variable selection and for the analytical processes outlined in this research. However, as a construct with multiple second order formative sub-dimensions, it is necessary to determine how the sub-dimensions is combined to form the focal resilience construct. As Goertz (2006) discussed, a critical part of a construct’s conceptualisation is the specification of the manner in which the sub-dimensions combine to give the construct its meaning. In the case of this model, the effect of each sub-dimension on the focal resilience construct is independent of the effects of the other sub-dimensions. This implies that a change in each individual sub-dimension is sufficient (but not necessary) to produce a change in the meaning of the focal resilience construct. The magnitude of the effect of each sub-dimension is unrelated to the other sub-dimensions and the sub-dimensions are substitutable in the sense that one might compensate for another. In this type of model, the sub-dimensions will be added together to form the focal construct. When all subcomponents are aggregated within an additive model, however, it is intended that the combination of constituent parts represent the resilience concept as a whole.

Different methods of weighting and aggregation have been investigated to find the best way of merging the identified indicators into an overall resilience index. Among the parametric and non-parametric methods of weighting methods in the literature (Nardo et al., 2005), PCA and EW have been employed in this study. The overall score calculated with each of these methods are highly correlated (r=0.91**). The effects of each method on the final neighbourhood scores are tested in detail in Chapter 7. Different methods are utilised for aggregation at different levels of the index. The subcomponent scores have been calculated by averaging the individual indicators' values to remove the effect of different number of variables in each subcomponent. The overall NDRI score and the scores of each dimension have been calculated using linear and geometric aggregation methods. However, the sensitivity of each method is examined in the next chapter.

Chapter 7
Index Validation

Sensitivity and Reliability Assessment



7. Index Validation - Reliability and Sensitivity Assessment

7.1. Overview

In Chapter 5, a set of resilience indicators at neighbourhood level was selected, and the refinement and purification steps were discussed in detail in Chapter 6. Moreover, the procedure of weighting and aggregating indicators to sub-indices and the overall NDRI were elaborated on in Chapter 6. This chapter seeks to evaluate the reliability and sensitivity of the proposed construct.

Research Question

- To what extent is the proposed model internally sound and robust?

Methodology

To explore the internal consistency and soundness of mathematical design of the proposed construct in detail, it has been analysed using correlation and sensitivity analysis (SA). The correlational analysis facilitates the decision-making on inclusion/exclusion of indicators; and sensitivity analysis assesses the degree of contribution and representativeness of indicators in each alternative construct developed in Chapter 6 with different weighting and aggregation methods. These analyses provide empirical evidence to measure the internal robustness of the indices and sub-indices.

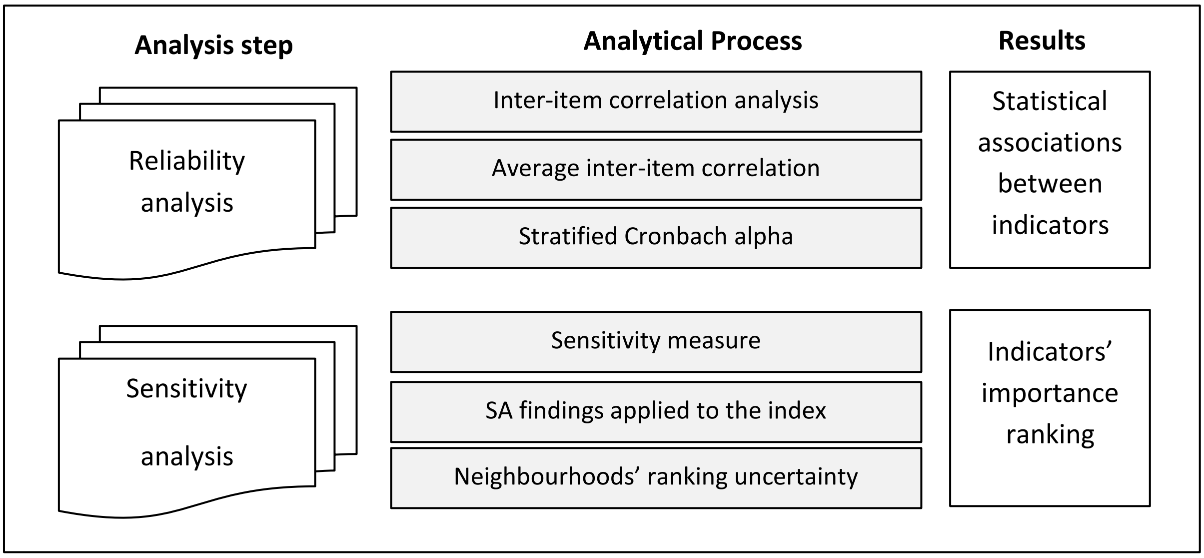


Figure 7.1 Flowchart of the analysis of Chapter 7

7.2. Reliability Analysis

Reliability assessment calculates the extent to which the indicators provide consistent results over repeated measurements (Babbie, 2013; Lo, 2013). In general, there are three main concerns in reliability analysis: equivalence, stability over time and internal consistency. As described in the methodology chapter, temporal stability is not the case in this study as theoretically the proposed measure is not expected to remain stable over time and across situations. Resilience measure is a dynamic issue over time, varying by dynamic variables over long period of time. On the other hand, retesting over short period of time would be meaningless as most of the data sources would be the same as the previous secondary sources. The equivalence reliability is covered in the validation chapter (Chapter 8) as it is the same as convergent validity. The Social Vulnerability index (SOVI) and Socio-Economic Index for Area (SEIFA) are utilised to test the equivalence reliability. The correlation between the alternative form and the Neighbourhood Disaster Resilience Index (NDRI) in equivalence reliability (convergent validity) shows if the measurement error in the present scale is considerable or not.

Internal consistency is not a necessary assumption for the intended construct as it is mainly a formative construct. However, checking the consistencies could facilitate the refinement and purification of the selected indicators, so indicators with very low or negative corrected item-correlation are removed from the construct (corrected item-total correlation is the correlation of an item with the total score of all other items in a construct). Two aspects of the internal consistency are reflected in this study (Brunner & SÜβ, 2005; Coltman et al., 2008): the share of the variance in each measurement item explained by the latent variable (individual item reliability), the amount of scale score variance that is accounted for by all underlying (composite reliability). In this chapter, the proper reliability assessments for each part are conducted using different methods explained below.

7.2.1. Individual Item Reliability

Individual item reliability captures the share of the variance in each indicator explained by the latent variable. In this section, considering the multi-dimensionality of the NDRI, the internal consistency of variables in unidimensional first order sub-components of the model has been investigated, but not for the whole model. The components which measure specific dimensions of resilience might show a low correlation with the other components' measures. For example, the NEcoRI includes variables chosen to capture economic resources and livelihood stability, while NSoRI focuses solely on the vulnerability of the population and their participation rate. There is a significant difference between the concepts measured by these two sub-indices and they do not share any common variables. Thus, there is no need to assess the internal consistency between these dimensions. Therefore, inter-item correlation is used to assess whether the sub-indices have the acceptable precision. Moreover, to make sure that the sub-indices have the adequate precision, another alternative of each sub-indice is developed, dropping the low/negative correlated variables from it. Later in the sensitivity section, the impact of their inclusion/exclusion on overall scores is examined.

Inter-Item Correlations

In a formative construct the indicators of each sub-component do not necessarily share the same theme and therefore have no preconceived pattern of inter-correlations. However, in this section the inter-item correlation among indicators for each component has been examined for the purpose of checking the directionality and further refinement of the selected indicators. The results are presented in the tables below for social (Table 7.1), economic (Table 7.2), physical (Table 7.3) and environmental (Table 7.4) components. These tables also include the item to total correlation (the correlation of the item to the summated scale score) to check the direction of causality of each indicator with the total score. Briggs et al. (1986) points out that the optimal level of homogeneity for reflective indicators occurs when the mean inter-item correlation is in the .2 to .4 range. Less than .1 shows that a single total score could not represent the complexity of the items and higher than .5 shows that the indicators might be overly redundant (Briggs & Cheek, 1986). This rule of thumb has been considered to further refine the indicators.

The inter-item correlation matrix presented in Table 7.1 reveals significant associations ($p<.05$, $p<01$) between NSoRI with social component's indicators. 'The percentage of population doing unpaid voluntary work' shows the strongest relationship ($r=0.756$). As it was expected, more than 82% of the social component indicators are positively and statistically significantly correlated ($p<.05$, $p<01$). The indicators of 'not vulnerable population', 'participation' and 'human capital' sub-components show the high level of internal consistency. While 'lace attachment' and 'access to resources' sub-components indicators show some inconsistencies. For example, the 'percentage of people who lived in the same address as 5 years ago' is negatively correlated with other indicators within the social component and therefore is removed from this component, as theoretically it was supposed to contribute positively to resilience in the same direction as the other indicators of this component (Cutter et al., 2010). In the same way, the inclusion of two more indicators in the index is reconsidered, as they showed negative or insignificant relationship with the index and the other indicators including: the percentage of the immigrants arrived before 2009 and the percentage of those with education higher than 8 years.

The result of the inter-item correlations for the economic component is presented in Table 7.2. 'SEIFA economic resources index' (explained in Chapter 4, page 68) and 'median house value' are negatively or insignificantly associated with other indicators and therefore they are removed from the second alternative NEcoRI index. In fact, variables number 6 and 9 are excluded from the index variables list to check the impact of this exclusion on the overall score of the index later in the sensitivity analysis section. Overall, more than 75% of the indicators of the economic sub-component are statistically significant and positively correlated. This result suggests that economic component has a moderate internal consistency.

In contrast with the social and economic component indicators, the physical component shows much less internal consistency. This was expected considering the formative nature of its sub-components. The physical component basically contributes to the capacity of the community to respond effectively in the event of a disaster and the emergency phase after the disaster. The correlation analysis showed there is no statistically significant correlation between three physical indicators with other indicators (including the percentage of services land use, the percentage of educational land use and the percentage of units with vehicle access). Therefore, these three indicators are removed from the indicators list to calculate the second alternative of the NPhyRI. Overall, more than 60% of the physical component indicators are positively and statistically significantly correlated.

Table 7.1: Inter-item correlation between social component indicators

	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000											
2	.549**	1.000										
3	.629**	.609**	1.000									
4	.192**	.542**	.498**	1.000								
5	-.446**	-.315**	-.283**	.135	1.000							
6	-.316**	.054	.094	.522**	.682**	1.000						
7	-.556**	-.230**	-.324**	.036	.650**	.607**	1.000					
8	.141*	.101	.106	.043	-.014	.012	-.080	1.000				
9	.212	-.065	.022	.093	.155	.399**	.638**	.105	1.000			
10	.251**	.413**	.686**	.485**	.085	.484**	.076	.003	.289**	1.000		
11	.422**	.730**	.642**	.449**	-.239*	..095	-.396**	.036	.058	.569**	1.000	
12	.562**	.805**	.673**	.426**	-.382**	-.002	-.544**	.078	.181	.547**	.756**	1.000
13	.391**	.694**	.749**	.666**	.022	.485**	-.089	.255*	.334*	864**	.764**	.774**

Note: * Correlation is significant at the 0.01 level (2-tailed);** Correlation is significant at the 0.05 level (2-tailed)

(1)% population age >5 and <65 (2) % non single parent families (3) % population not need assistance (4) % population not renting public housing (5) % population living in the same address 5 years ago (6) % home owner (7) % migrants arrived before 2009 (8) % education higher than 8 years (9) % population with sufficient English (10) % unpaid voluntary work (11) % volunteers (12) human capital index (from SEIFA index) (13) NSoRI

Table 7.2: Inter-item correlation between economic component indicators

	1	2	3	4	5	6	7	8	9	10	11
1	1.000										
2	.155	1.000									
3	.139	.765**	1.000								
4	.108	.956**	.716**	1.000							
5	-.108	.107	-.061	.121	1.000						
6	.121	.547**	.529**	.617**	.032	1.000					
7	-.083	.580**	.795**	.547**	.010	.424**	1.000				
8	.098	.179	.078	.175	.139	-.042	.071	1.000			
9	.004	.267**	.435**	.236*	.088	.051	.391**	-.285**	1.000		
10	.075	-.044	.006	-.012	.101	.151	.004	.073	-.032	1.000	
11	.706**	.626**	.696**	.572**	.121	.339**	.566**	.003	.066	.121	1.000

Note: * Correlation is significant at the 0.01 level (2-tailed);** Correlation is significant at the 0.05 level (2-tailed)

(1) % commercial buildings constructed post 1981 (2) % population employed (3) median household income (4) % female labour force participation (5) median house value (6) % healthcare and social services employees (7) % financial and insurance services (8) economic resources (SEIFA index) (9) % population not employed in primary industries (10) # retail centres per 10,000 (11) NEcoRI

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	1.000																				
2	-.141	1.000																			
3	.185	.032	1.000																		
4	.26*	-.003	-.35**	1.000																	
5	.061	.031	.080	.057	1.000																
6	.208*	.052	-.146	.41**	.167	1.000															
7	.129	-.122	-.19**	.172	-.005	-.037	1.000														
8	-.073	-.045	-.004	.194*	.038	.209**	.306**	1.000													
9	.140	.141	-.175	.137	.116	.299**	.330**	.407**	1.000												
10	-.054	-.208*	-.162	.005	.016	.071	.218**	.151	.121	1.000											
11	.113	-.024	-.106	.39**	.097	.382**	.188	.636**	.353**	.189	1.000										
12	.076	-.120*	.107	.116	-.070	.031	.189	.113	-.066	.243*	.066	1.000									
13	-.040	.042	-.147	.176	-.097	.059	.014	.298**	.138	.023	.141	.062	1.000								
14	.135	.037	-.016	.037	-.084	.081	.054	.239**	.094	.292**	.21*	.277**	.206*	1.000							
15	.086	.027	-.064	.124	-.062	.206*	.281**	.271**	.164	.347**	.272**	.171	.278**	.328**	1.000						
16	-.29**	.018	-.-93	.395**	.159	.351**	.274**	.874**	.521**	.155	.66**	.170	.299**	.227**	.310**	1.000					
17	.123	-.113	.146	-.118	-.085	-.175	-.05	-.118	-.105	-.037	-.142	-.050	-.096	-.196*	-.28**	-.159	1.000				
18	.122	.113	-.146	.118	.085	.175	.050	.118	.105	.037	.142	.050	.096	.196*	.28**	.159	-.998*	1.000			
19	.100	.039	-.086	-.076	.204*	-.140	.340**	.005	-.021	.064	.166	.046	-.065	.061	.181	-.006	-.112	.112	1.000		
20	.058	.166	.28**	-.22*	.133	-.041	.034	-.174	-.153	.026	-.179	-.024	.107	.151	.198*	-.091	-.059	.059	.358**	1.000	
21	-.35**	-.013	-.38**	.882**	.098	.387**	.199**	.317**	.222*	.028	.446**	.158	.227*	.049	.125	.501**	-.169	.169	-.097	-.23**	1.000
22	-.08	-.034	.21**	.415**	.139	.076	.323**	.438**	.141	.156	.219*	.030	.223*	.184	.240*	.463**	-.153	.153	.515**	.132	.424**
23	-.49**	.013	-.36**	.603**	-.039	.295**	-.011	.244*	.236*	.015	.373**	.100	.048	-.133	-.101	.307**	-.029	.029	-.31**	-.54**	.565**
24	.039	.182	.106	.573**	.303**	.427**	.218**	.287**	.219*	.045	.385**	.020	.237*	.335**	.323**	.451**	.156	.159	.257*	.05	.379**

(1) % non built-up area in flood zone (2) % land public services in flood area (negative impact) (3) % building constructed post 1981 (4) % not single family detached houses (5) # ambulance services per 10,000 (6) # hospitals per 10,000 (7) # schools per 10,000 (8) recreation land per 10,000 (9) # education facilities per 10,000 (10) # sport facilities per 10,000 (11) % dwellings with internet access (12) # places of worship per 10,000 (13) # police stations per 10,000 (14) # fire services per 10,000 (15) # SES per 10,000) (16) % service land per 10,000 (17) % units with motor vehicle access (18) % units with vehicle (19) road intersections density per 10000 (20) principle road km (21) building type diversity (22) land use mix (23) dwelling density (24) NPhyRI

The length of a river along the neighbourhood is removed from the environment component as it had empirically negative/insignificant relationships with other indicators and moreover, theoretically it may or may not contribute to the flood impact on neighbourhoods depending on the topography of the area. For example, in the case of Brisbane neighbourhoods, Saint Lucia and Kangaroo Point area situated along almost the same length of river but they had completely different levels of flood impact because of their altitude. The percentage of developed open spaces in flood risk areas and hazard frequency show negative/insignificant correlation with most of the other indicators. Therefore these three indicators are dropped from the indicators list to calculate the second alternative, NEnvRI.

Table 7.4: Inter-item correlation between environment component indicators

	1	2	3	4	5	6	7	8
1	1.000							
2	.953**	1.000						
3	-.171	-.116	1.000					
4	-.307**	-.330**	-.276**	1.000				
5	.095	.190	-.426**	.207*	1.000			
6	-.855**	-.818**	.282**	.240*	.040	1.000		
7	-.247*	-.214*	.145	-.085	.001	.228*	1.000	
8	.546**	.531**	-.388**	.487**	.478**	-.507**	-.255*	.1.000

Note: * Correlation is significant at the 0.01 level (2-tailed);** Correlation is significant at the 0.05 level (2-tailed)

(1)% land not in flood risk area (2) % residential land not in flood area (3) riverside (km)_negative (4) % wetland/marsh land in flood risk area (5) % pervious land (6) % developed open space in flood risk area (7) hazard frequency - three times flooded (8) NEnvRI

Average Inter-Item Correlation

The average inter-item correlation is also performed using the correlations of all of the items in the indices that are designed to measure the same construct. The correlation between each pair of items has been computed first, as illustrated in Tables 7.1, 7.2, 7.3 and 7.4. Then the average inter-item correlation was simply calculated as the average of all these correlations. The highest average inter-item correlation is exhibited by economic sub-index (0.396) followed by social sub-component, e component (0.175) and physical component (0.036). Considering the formative nature of the construct, these low scores of average inter-item reliability were not surprising. However, the positive scores suggest that the indicators of each sub-dimension are in the same direction and are consistent with each other.

7.2.2. Composite Reliability of the Overall Scale

There is a relative dearth of research on assessing the reliability of composite scores. However, it is necessary to understand how combining scores affects reliability. Composite reliability is the overall reliability of the composite index which is a collection of heterogeneous but similar items (Brunner & SÜβ, 2005). It calculates the total amount of true score variance in relation to the total scale score variance, and corresponds to the conventional notion of reliability in terms of classical test theory.

Several methods exist for estimating the reliability of a composite score including the Stratified α (Cronbach et al., 1965), the Kristof/Feldt-Gilmer coefficient (Kristof, 1974; Gilmer & Feldt, 1983), maximal reliability (Li, Rosenthal, & Rubin, 1996), McDonald's ω (McDonald, 1970, 1999), multidimensional ω (Kamata et al., 2003), and Raykov's (1997, 2002) structural equation modelling (SEM) approach. Zimmerman et al. (2001) pointed out that if the sub-dimensions scores that make up the composite do not assess the same underlying dimension, several of these reliability coefficients have been found to be biased; they suggest exceptions to this are the stratified α, maximal reliability, multidimensional ω, and the SEM approach of Raykov. On the other hand, Kamata et al. (2003) found that stratified α, when directly compared with maximal reliability and multidimensional ω under five different multidimensional factor-structure, mostly performed the best. As such, in this thesis the Stratified α is utilised for assessing the composite reliability of the composite index.

Stratified Cronbach Alpha Coefficients of the NDRI Sub-indices

Considering the multidimensional nature of the NDRI, and in order to calculate the composite reliability of the scale, stratified alpha is an appropriate estimation method (Crawford et al., 2012). It assumes k components, where component (i = 1,…., k) consisted of sub-components. Stratified α is calculated by:

$$\alpha_s = 1 - \frac{\sum_{i=1}^{k} \sigma_i^2 (1 - \alpha_i)}{\sigma_x^2}$$

Where σ_i^2 and α_i are the variance and coefficient alpha, respectively, for the i_{th} subtest. In fact, when the correlations between items in the same subtest are higher than the correlations across items in different subsets, stratified alpha provides a better estimate than coefficient alpha (Rambaldi & Rao, 2011).

Multidimensional formative scales do not need to meet any precise reliability requirements (Bollen & Lennox, 1991; Kamata et al., 2003). However for evaluating stratified alpha and also to check the preliminary consistency and directionality of indicators, Cronbach alpha was calculated by the equation below for each sub-component (Dimitrov, 2014):

$$\alpha = \frac{N}{N-1}\left(1 - \frac{\sum \sigma^2 (Y_i)}{\sigma_x^2}\right)$$

Where N is equal to number of variables; $\sum \sigma^2 (Y_i)$ is equal to the sum of variables variances; and σ_x^2 is equal to the variance of the total composite.

The range of Cronbach's alpha coefficients is from zero to one. Perfect reliability can be denoted by coefficient one and coefficient zero represents a very unreliable measure. The acceptable level of alpha depends on the purpose of scale; for more rigorous measures, the rule of thumb for an acceptable level of alpha is 0.80 (Fletcher, 2013) while for less strict applications and also for early stages of research, Cronbach's alpha coefficient approaching 0.70 is also acceptable (Sterbenz et al., 2011). Given the fact that resilience as the main concept at the core of this research is at the early stage, thus it is reasonable to accept the alpha reaching 0.70 as a basic standard to determine the reliability of the overall index and sub-indices for the current model.

As noted in Chapter 5, the conceptual framework and matrix was used to guide the indicators selection process which includes the four dimensions of physical, social, economic and environmental. Each component contains different domains related to different attributes of resilience as shown in Table 5.1. Therefore, the reliability analysis is focused on maximizing the Cronbach's alpha coefficients for those theoretically unidimensional sub-components. In fact, variables that appeared not to perform well enough were dropped from the scale until the Cronbach's alpha reached a reasonable and acceptable level for unidimensional components.

Cronbach's alpha procedure generally returns two raw and standardized coefficients. Raw alpha is based on correlations, while standardized is based upon item covariance. The results in this study show higher scores for standardized alpha scores. The results show that the highest Cronbach's alpha coefficient is exhibited by economic livelihood and stabilities sub-indices (alpha = 0.936), followed by not vulnerable population (alpha = 0.723), physical- urban built form (alpha=0.769), economic sub-index (alpha = 0.749), economic- asset exposure (alpha= 0.741), social-, economic- access to resources (alpha= 0.678), social- place attachment (alpha=0.653), physical- access and evacuation potential (alpha= 0.581), economic- resource equity (alpha=0.558). These sub-indices reveal a relatively high level of internal consistency, which implies that these measures are reliable. Moreover, according to Table 7.5, the lowest alpha is shown by three subindices: human capital (alpha = 0.245), participation (alpha =0.419), economic diversity (alpha = 0.139), medical, shelter, response and reconstruction capacity. Based on the rule of thumb for the threshold of a Cronbach's alpha coefficient of about 0.70, these alpha coefficients are relatively low. From a reliability analysis point of view, these results imply that these measures have comparatively low precision, but as mentioned earlier, considering the formative structure of the index, they are acceptable for this type of exploratory research.

Stratified Cronbach's Alpha Coefficients of NDRI

The acceptable level of reliability depends on the purpose of indices and how they are going to be used. Raykov (1998) suggests that for the initial stages of modelling, Cronbach's coefficient of 0.7 or higher is sufficient. For research purposes, it is recommended that the composite reliability for indices be above the 0.50 threshold (Hair et al., 2006).

Table 7.5. Stratified Cronbach alpha scores for NDRI and its components

Components and sub-components of the model	#indicators	Variance	Alpha
Social	12	EW=.25	.792
Not vulnerable population	4	.64	.838
Place attachment	3	.70	.764
Participation	2	.45	.513
Economic	11	EW=.18	.709
Economic & livelihood stabilities	3	.35	.936
Economic diversity	2	1	1
Resource equity	3	.40	.674
Physical	23	EW=.10	.556
Medical capacity	2	.54	.641
Temporary sheltering capacity	5	.26	.553
Emergency response capacity	3	.19	.642
Urban form	3	.67	.724
Environmental	7	EW=.52	.506
Risk and exposure	3	.012	.595
Protection resources	3	.14	.607

7.3. Sensitivity Analysis

The correlational analysis in the previous section facilitates the internal consistency assessment and also the exclusion of some inconsistent variables. However, it could not prove the relative importance of the indicators. Moreover, a number of subjective choices were made during the development of composite indicators, including the indicators' selection, normalisation and weighting and aggregation methods. Therefore, in this section a combination of uncertainty and sensitivity analysis is used to evaluate the robustness of the composite indicators and improve its structure. All of the sub-indices and the overall NDRI undergo sensitivity analysis to identify the relevant parsimony indicators and to see whether the proposed conceptual framework provides an appropriate fit to the data.

Uncertainty analysis evaluates how the uncertainty sources in input data could disseminate in the composite indicators' structure and final score, while sensitivity analysis focuses on the effect of individual sources of uncertainty on the final score's variance (Schmidtlein et al., 2008). Sensitivity analysis is thoroughly linked to uncertainty analysis. In this study, a combination of the sensitivity and uncertainty analysis is performed to assess the robustness of the index to uncertain inputs as below:

- Inclusion and exclusion of the urban form indicators
- Using alternative weighting systems including PCA and EW weighting systems
- Using different aggregation schemes including linear and geometric systems

In this research, standardised regression coefficient are utilised as sensitivity measures, considering the correlation of input factors from the previous section and also the structure of the index. This method is suitable as the evaluated index is linear and the regression fit (R2) always exceeds 0.65, according to the threshold suggested by Liepmann and Stephanopulos (1985). On the other hand, Saisana et al.'s (2005) proposed rule of thumb (Si > 1/k) is used as a threshold of the output variance where k represents the number of input factors.

7.3.1. Social Component

The initial correlational assessment for social component is confirmed by the sensitivity analysis in this section. As previously mentioned, the sensitivity measure in this study is the standardised regression coefficient. The rule of thumb suggested by Saisana et al. (2005) is used as a threshold for diagnosing the importance of the indicator. They suggest Si> 1/k as the threshold for indicator's importance that k represents the number of indicators. Therefore, for NSoRI's indicators, the 'importance' threshold is Si > 1/12 (or 0.08). Based on the results of the sensitivity analysis, the SEIFA human capital index dominates the social sub-indices (Si= 0.481) followed by percentage volunteers (Si=0.237).

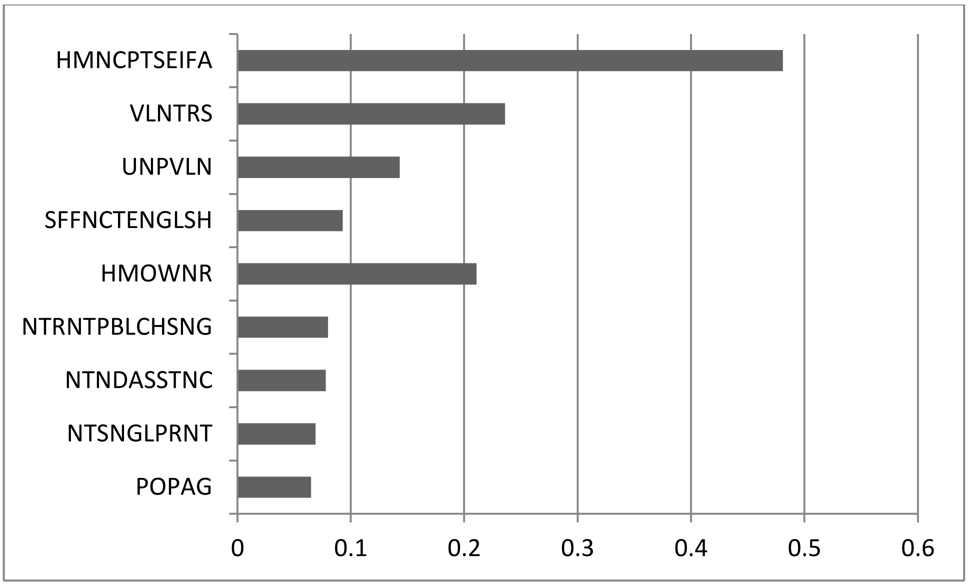


Figure 7.2. Sensitivity measures of Neighbourhood Social Disaster Resilience

*Standardised regression coefficients are significant ($p<0.01$,n=76, $R^2=0.99$)

Three more alternatives are calculated for the Neighbourhood Social Resilience Index based on the inclusion/exclusion of the inconsistent indicators and alternative weighting and aggregation schemes. NSoRI_2 is created by only 9 indicators, excluding the indicators which fell short of the importance threshold and correlational inconsistencies (including the percentage of residents living in the same address as 5 years ago, the percentage of immigrants who arrived before the last two years and the percentage of the population with education higher than 8th year). Although they showed high commonality in PCA and MDSA, they seem to have a negative effect on the reconstruction process. Specifically, the percentage of the population who lived at the same address 5 years ago and the percentage of migrants who arrived before 2009, have statistically negative correlation with the percentage of recovery within 10 and 13 months. Theoretically, they are expected to show place attachment and contribute to disaster resilience, but in this case study this is not so. This can be attributed to their negative correlation with economic stability factors in this case study area. Therefore, they are omitted in the second alternative of NSoRI. NSoRI_PCA is an alternative in which the sub-components are weighted based on principle component analysis. NSoRI_Geo is the alternative index with a geometric aggregation scheme.

Altering the aggregation scheme causes about two rank changes in fifty percent of the neighbourhoods. Saint Lucia shows the most extreme change in ranking (13) by altering the aggregation method. The neighbourhood is catapulted from rank 39 to rank 20. This can be due to moderate compensability in geometric aggregations method. Considering the fact that the scores of sub-components for Saint Lucia are differing to a wide degree, it could be expected that compensability would have a large effect on the final aggregated score.

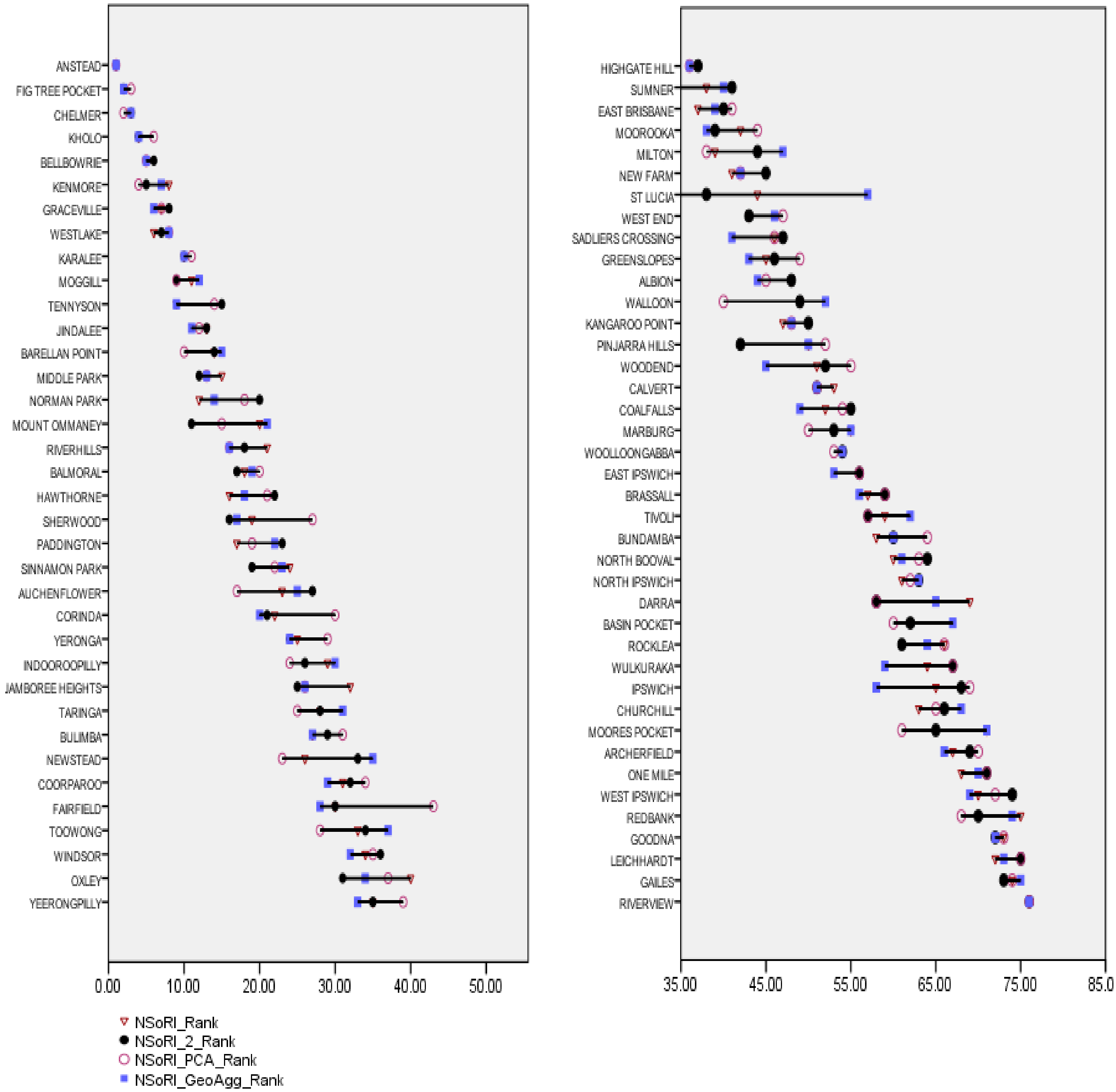


Figure 7.3. Alternative Neighbourhood Social Resilience Index ranking

Table 7.6. Sensitivity analysis and correlation analysis findings applied to NSoRI

	NSoRI	NSoRI_2	NSoRI_PCA	NSoRI_Geo
Top five neighbourhoods	Anstead Fig Tree Pocket Chelmer Kholo Bellbowrie	Anstead Fig Tree Pocket Chelmer Kholo Kenmore	Anstead Chelmer Fig Tree Pocket Kenmore Bellbowrie	Anstead Fig Tree Pocket Chelmer Kholo Bellbowrie
Bottom five neighbourhoods	Riverview Redbank Gailes Goodna Leichhardt	Riverview Leichhardt West Ipswich Gailes Goodna	Riverview Leichhardt Gailes Goodna West Ipswich	Riverview Gailes Redbank Leichhardt Goodna
#Indicators	12	9	9	9
Median rank change		2	2	2
Range rank change		0-11	0-13	0-19
The most extreme change		Darra 8-19-19-12	Fairfield 47-47-34-49	Saint Lucia 33-39-45-20
90^{th} percentile rank changes		6	6	6

NSoRI_2 generates a ranking which differs from the original ranking on average by 2 ranks (median rank change =2). On the other hand, ninety percent of the 76 neighbourhoods have 6 or fewer changes in their ranking. Darra, with eleven rank changes, has the highest rank change. Therefore, NSoRI_2 could result in the fairly similar resilience assessment as NSoRI.

Most of the changes between the four alternatives of NSoRI occur in the mid-ranks of the neighbourhoods (Figure 7.3). This means that NSoRI and its alternatives are stable in regards to the most and the least resilient neighbourhoods. Overall, NSoRI_2 shows appropriate construct validity and the representation of sub-index's indicators seems balanced as the SA reveals acceptable sensitivity levels as a result of the indicators reduction. The decision to weight the sub-components based on PCA or EW or using geometric aggregation method does not have a significant impact on the NSoRI's ranking output (Table 7.6). Therefore, considering that there is no theoretical reason to weight these sub-components differently, equal weighting and linear aggregation (NSoRI_2) are used in this case to calculate the neighbourhood social disaster resilience index.

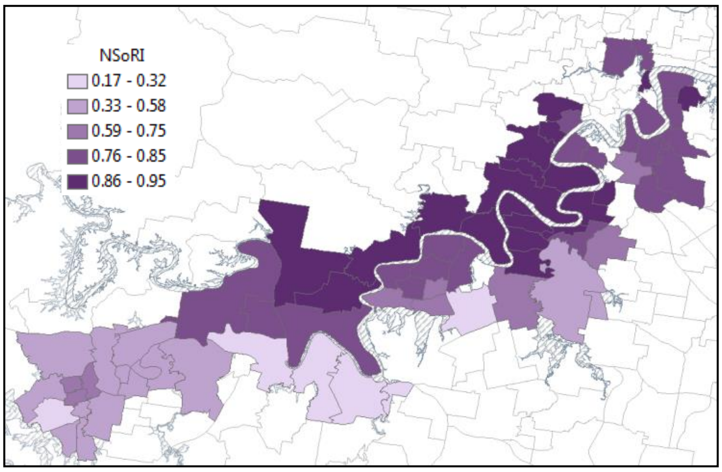


Figure 7.4. Neighbourhood Social Resilience Index for the Brisbane study area

7.3.2. Economic Component

The sensitivity analysis demonstrates that indeed eleven out of twelve indicators of economic resilience are significant. The percentage of commercial land use in flood areas has no significant effect on the overall index and is excluded from the second alternative of NEcoRI. The percentage of commercial buildings built after 1981 shows the strongest sensitivity measure (S_i=0.627) and all other indicators positively and significantly contribute to the overall NEcoRI index.

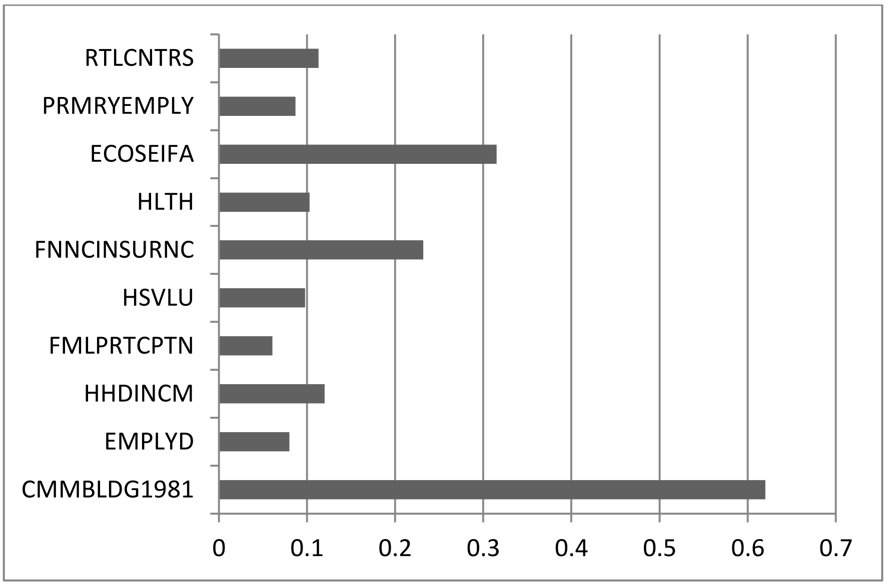


Figure 7.5. Sensitivity measures of Neighbourhood Economic Disaster Resilience

*Standardised regression coefficients are significant ($p<0.01$, n=76, $R2=0.94$)

Three other alternative versions of NEcoRI are calculated and evaluated in terms of their sensitivity to inclusion and exclusion of indicator, weighting and aggregation system. The results are presented in Table 7.7. Alternative index designs of NEcoRI produce approximately similar results. The NEcoRI_2 shows that Fig Tree Pocket, Norman Park, Moggill, Westlake and Auchenflower are economically resilient neighbourhoods and West Ipswich, Riverview, Ipswich, Calvert and Marburg are the least economically resilient neighbourhoods. Therefore, both NEcoRI and NEcoRI_2 identify an almost identical set of highly economically resilient neighbourhoods; however, they differ to some extent in the determination of low resilient neighbourhoods.

Table 7. 7. Sensitivity analysis and correlation analysis findings applied to NEcoRI

	NEcoRI	NEcoRI_2	NEcoRI_PCA	NEcoRI_Geo
Top five neighbourhoods	Fig Tree Pocket Mount Ommaney Auchenflower Norman Park Middle Park	Fig Tree Pocket Norman Park Moggill Westlake Auchenflower	Norman Park Fig Tree Pocket Balmoral Kenmore Auchenflower	Mount Ommaney Fig Tree Pocket Fairfield Moggill Karalee
Bottom five neighbourhoods	West Ipswich Riverview Marburg Churchill Calvert	West Ipswich Riverview Ipswich Calvert Marburg	Riverview West Ipswich Gailes Goodna Ipswich	Calvert Kenmore West Ipswich Marburg Riverview
#Indicators	11	10	10	10
Median rank change				
Range rank change		2	8	6
The most extreme change		16 Redbank, Greenslopes	42 Kenmore	36 Redbank
90th percentile rank changes		7	18	14

The median rank change of the NEcoRI alternatives is 2 for the ‘reduced’ version, 8 for the ‘PCA weighted’ version and 6 for the ‘geometric aggregated’ version. Ninety percent of the neighbourhoods change less than 7 ranks for NEcoRI_2, less than 18 ranks for PCA-weighted index and 14 ranks for geometric aggregated index. Redbank (36), Kenmore (42) and Greenslopes (16) show the most extreme changes in the index alternative rankings. Generally, the rank changes are limited and are not concentrated in either low or high resilient neighbourhoods. Hence the decision to weight or not to weight the indicators has significant implications for the NEoRI’s output, using the PCA weighting and geometric aggregation is refrained from in calculating the neighbourhood economic resilience index.

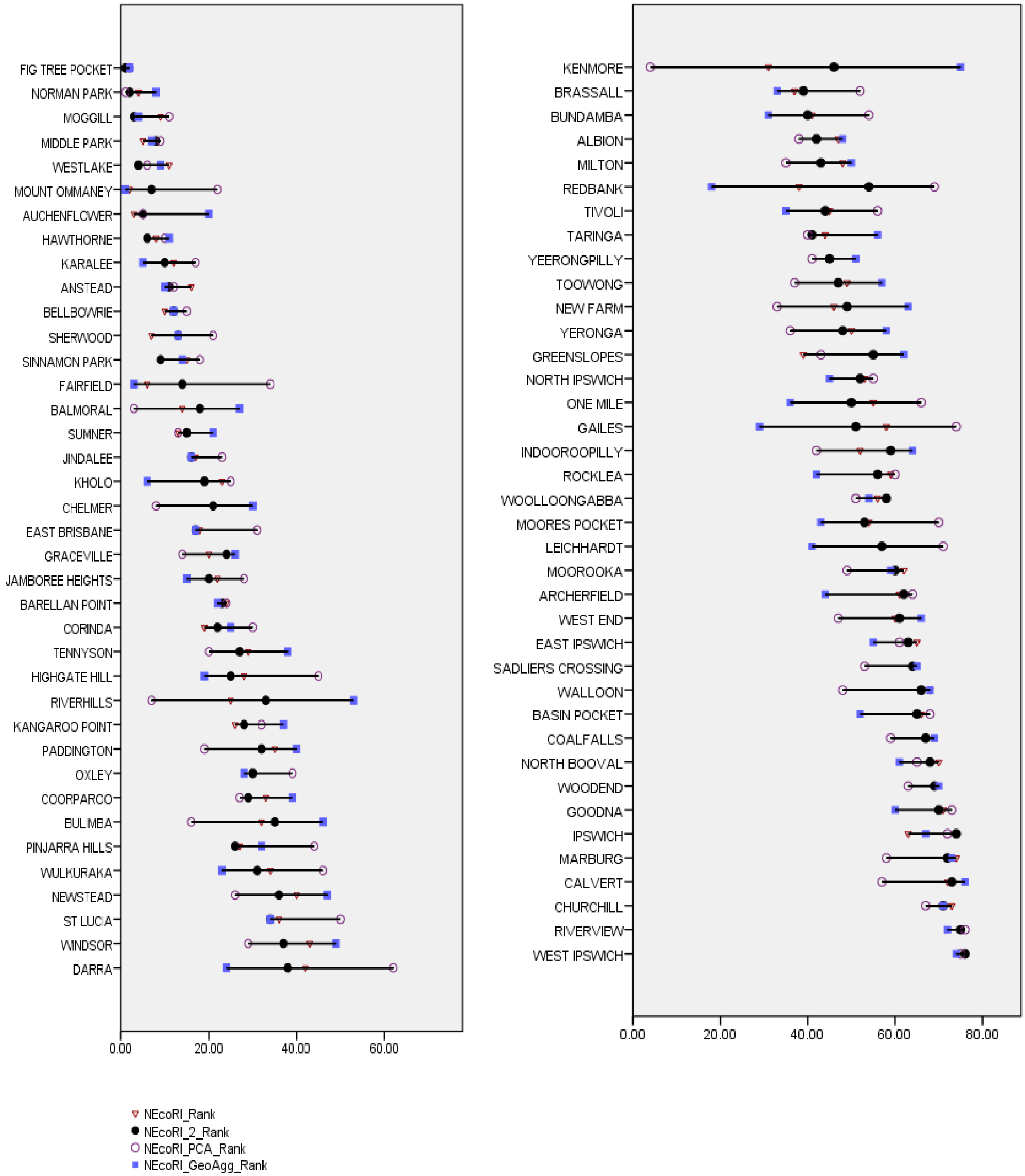


Figure 7.6. Alternative Neighbourhood Economic Resilience Index ranking

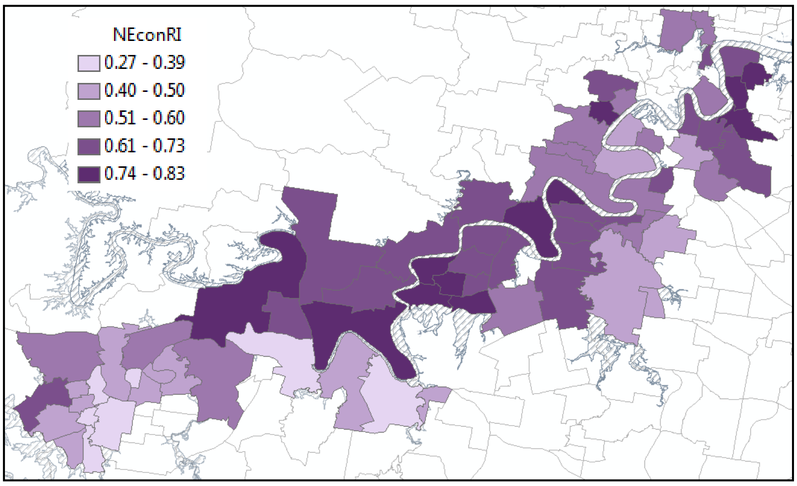


Figure 7.7. Neighbourhood Economic Resilience Index for the Brisbane study area

7.3.3. Physical Component

The sensitivity analysis performed in this section extracted the sensitivity of NPhyRI to variations in inclusion and exclusion of indicators, weighting and aggregation systems. Three least associated indicators in physical components identified from correlation analysis are excluded from the second alternative of NPhyRI (including the percentage of services land use, the percentage of educational land use and the percentage of units with vehicle access). Moreover, three urban form factors are excluded as well, since they show no significant relationship with recovery outcomes (see Chapter 8). This exclusion creates 10.5 median rank changes ranging from 0 to 43. On the other hand, PCA based weighting versus equal weighting system causes a median rank change of 7 which ranges from 0 to 44. Geometric aggregation versus linear aggregation causes only one rank change on average. The most extreme volatility occurs in in mid ranked neighbourhoods.

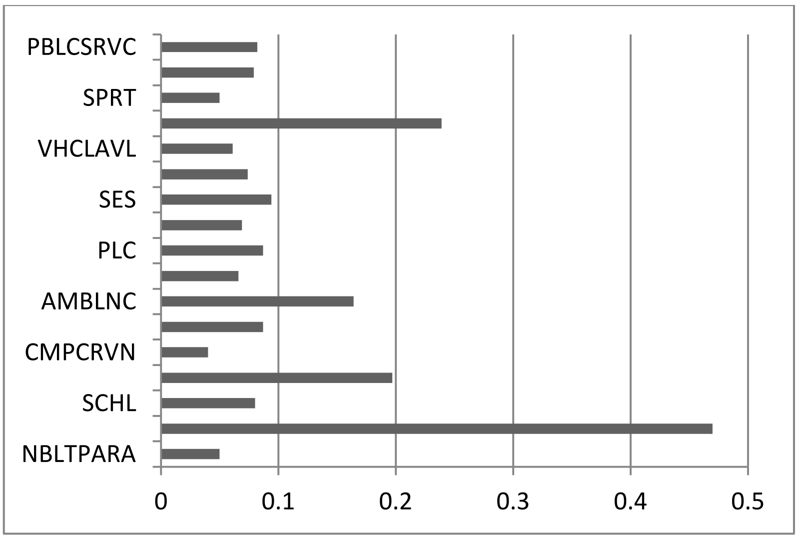


Figure 7.8. Sensitivity measures of Neighbourhood Social Disaster Resilience
*Standardised regression coefficients are significant ($p<0.01$, $n=76$, $R^2=0.99$)

Figure 7.8 shows the indicators' importance assessment results, which along with the correlation matrix in the reliability assessment section, were the key to simplifying the index from 23 indicators to 17 indicators. The threshold for indicators' importance is S_i= 1/17 = 0.06 and all of the NPhyRI_2 indicators exceed this threshold (Figure 7.8). This legitimises the inclusion of these 17 indicators. Alternative aggregation systems with these 17 indicators generate more or less identical scores. Ninety percent of the neighbourhoods change their rank by less than two ranks. However, alternative weighting systems perform differently, with average position changes of seven spots and ninety percent of neighbourhoods changing their positions by less than 23 ranks (Table 7.8).

Table 7.8. Sensitivity analysis and correlation analysis findings applied to NPhyRI

	NPhyRI	NPhyRI_2	NPhyRI_PCA	NPhyRI_Geo
Top five neighbourhoods	Tivoli Leichhardt Archerfield Jamboree Heights Sinnamon Park	Sinnamon Park Jamboree Heights Tivoli Yeronga Leichhardt	Fig Tree Pocket Leichhardt Tivoli Barellan Point Sinnamon Park	Sinnamon Park Tivoli Jamboree Heights Yeronga Leichhardt
Bottom five neighbourhoods	Tennyson Woolloongabba Wulkuraka Newstead Darra	Brassall East Ipswich Chelmer Fairfield Calvert	Brassall East Ipswich Chelmer West End Riverview	Brassall East Ipswich Chelmer Fairfield Calvert
#Indicators	23	17	17	17
Median rank change		10.5	7	1
Range rank change		0-43	0-44	0-5
The most extreme change		Brassall	Riverview	Gailes, Yeerongpilly
90^{th} percentile rank changes		26	23	2

Considering the ranking results of the four alternatives, the NPhyRI_2 equally weighted and linearly aggregated index is a sound method for developing this sub-index. This design counts all of the important indicators in the physical index and represents all of its sub-components.

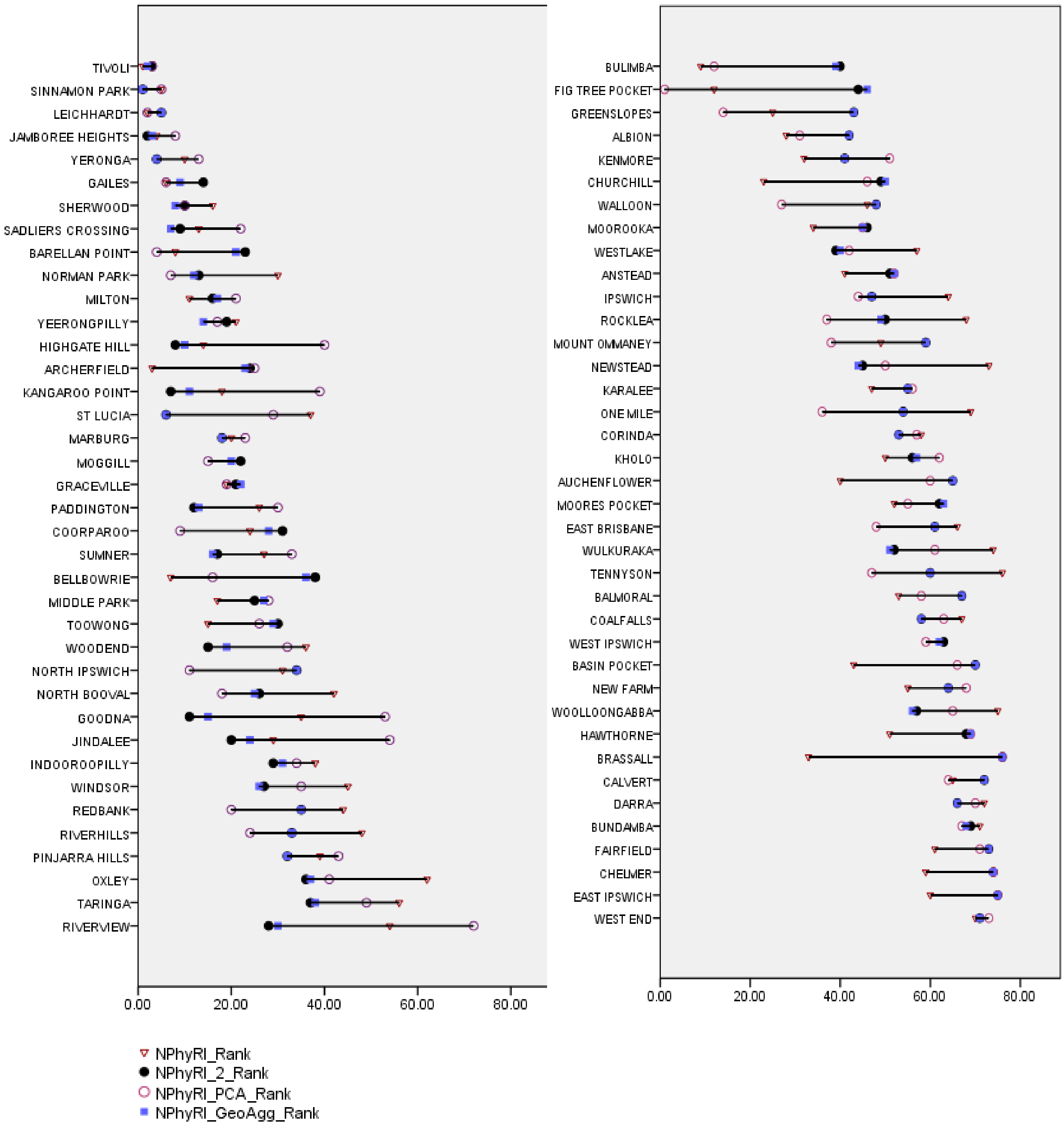


Figure 7.9. Alternative neighbourhood physical resilience index ranking

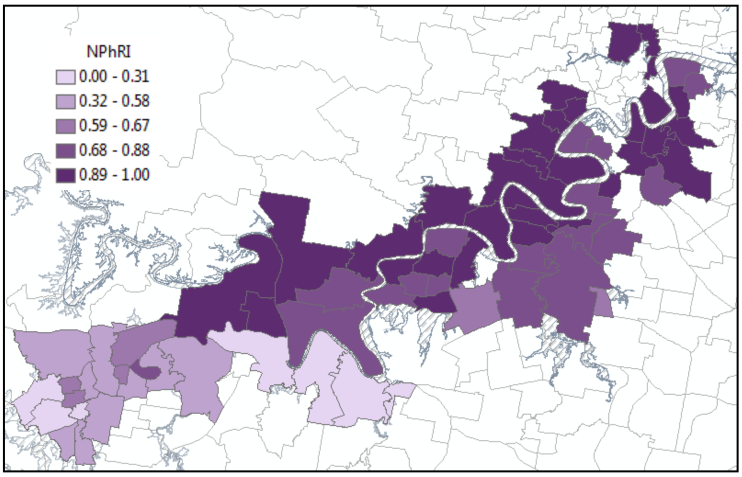


Figure 7.10. Neighbourhood Physical Resilience Index for the Brisbane study area

7.3.4. Environment Component

The sensitivity analysis for the environment component reveals that the percentage of wetland/marsh land in the flood risk areas has the highest importance score (S_i=1.04). However, the other three indicators, including the percentage of pervious land in flood risk areas, the percentage of residential land in flood risk areas, and the percentage of a neighbourhood's land not in flood risk areas do not exceed the sensitivity threshold (1/4=0.25). Similarly to other components, four alternatives of this component are evaluated for robustness of the index.

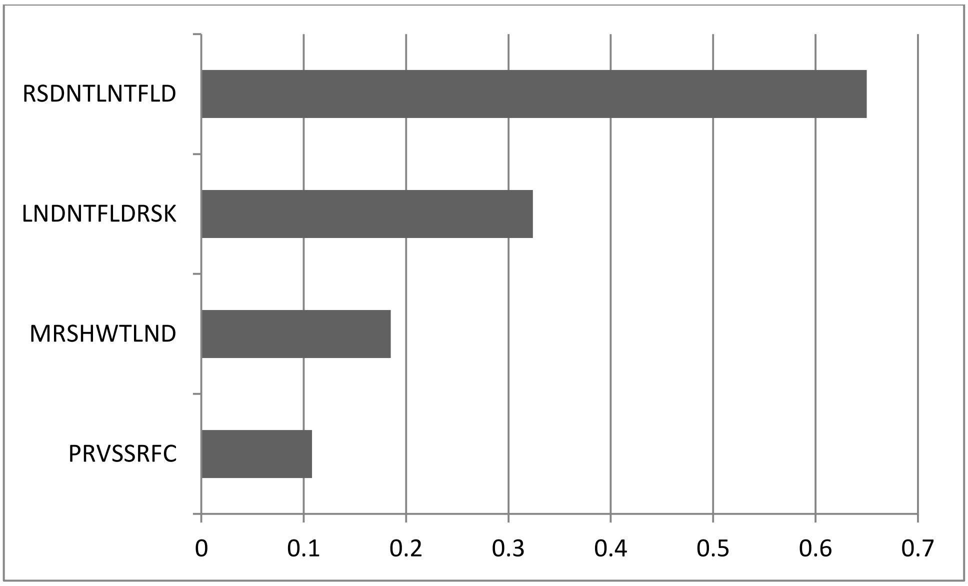


Figure 7.11. Sensitivity measures of Neighbourhood Environmental Resilience Index

*Standardised regression coefficients are significant ($p<0.01$, n=76, R^2=0.93)

Dropping the negatively and insignificantly related indicators has a dramatic impact on the ranking of the neighbourhood, with zero to sixty seven changes in some neighbourhoods' positions (Table

7.9). For example, Kholo ranks 73 in NEnvRI, while this suburb moves up to the top five by rank 4 in NEnvRI_2. Therefore, the first alternative is discarded from the list of NEnvRI alternatives due to high levels of sensitivity. On the other hand, changing the weighting and aggregation system from equal weighting to PCA, and from linear to geometric aggregation, has a very low impact on the overall ranking by only 1 median rank change. By changing the aggregation scheme, ninety percent of the neighbourhoods change their comparative resilience position by six ranks or less.

However, the robustness of the most and the least resilient neighbourhoods is confirmed as the neighbourhoods at the top five and bottom five of the ranking list are the same in the last three alternatives of NEnvRI.

Table 7.9. Sensitivity analysis and correlation analysis findings applied to NEnvRI

	NEnvRI	NEnvRI_2	NEnvRI_PCA	NEnvRI_Geo
Top five neighbourhoods	Yeerongpilly Albion Basin Pocket Bundamba Indooroopilly	Calvert Anstead Walloon Kholo Wulkuraka	Calvert Walloon Anstead Kholo Wulkuraka	Calvert Anstead Walloon Kholo Moggill
Bottom five neighbourhoods	Westlake Riverhills Rocklea Bulimba Archerfield	Rocklea Fairfield Graceville Archerfield Bulimba	Rocklea Fairfield Graceville Archerfield Bulimba	Rocklea Fairfield Graceville Archerfield Bulimba
#Indicators	7	4	4	4
Median rank change		12.5	1	1
Range rank change		0-67	0-20	0-12
The most extreme change		Kholo	Sumner	Bellbowrie
90^{th} percentile rank changes		40	3	6

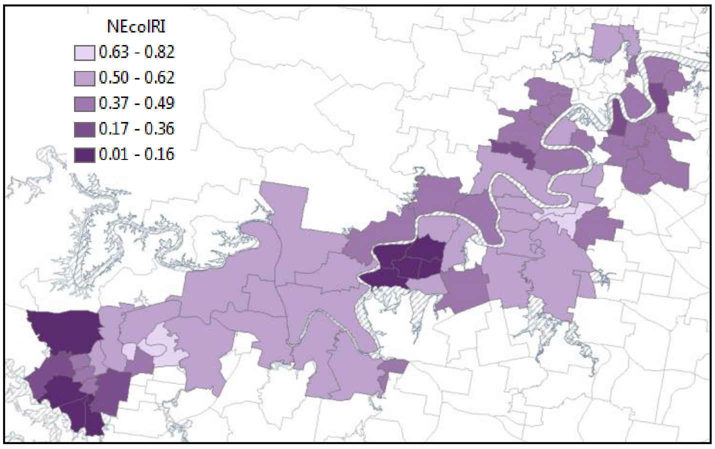


Figure 7.12. NDRI for the Brisbane study area

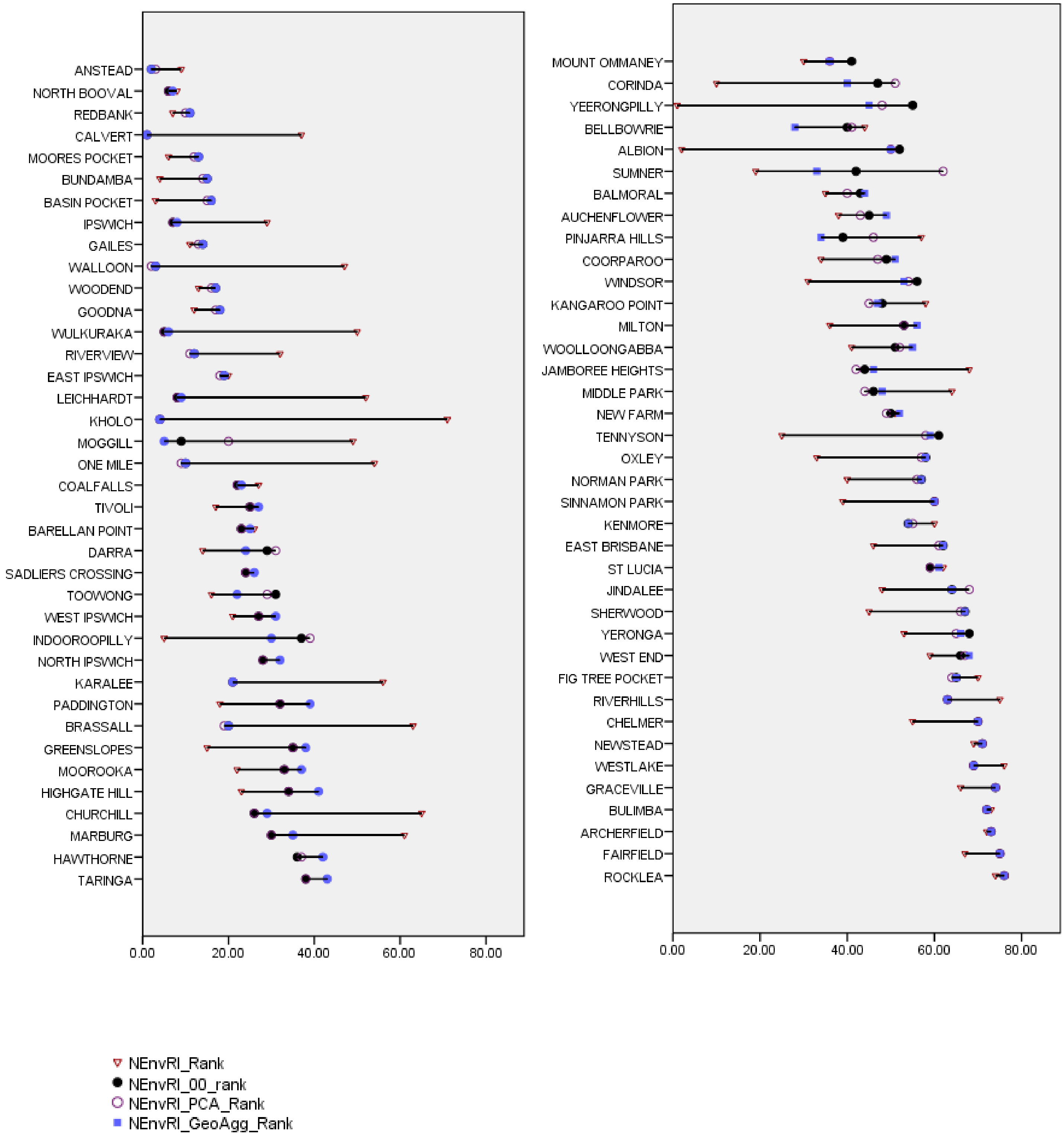


Figure 7.13. Alternative NDRI ranking

7.3.5. NDRI

Two alternatives have been calculated for NDRI by combining the alternative components by linear and geometric aggregation methods. The sensitivity measure for NDRI shows that all components are important and exceed the sensitivity threshold (1/4=0.25). However, neighbourhood social resilience has the highest standardised coefficient followed by economic and environment components. Physical component has the lowest coefficient.

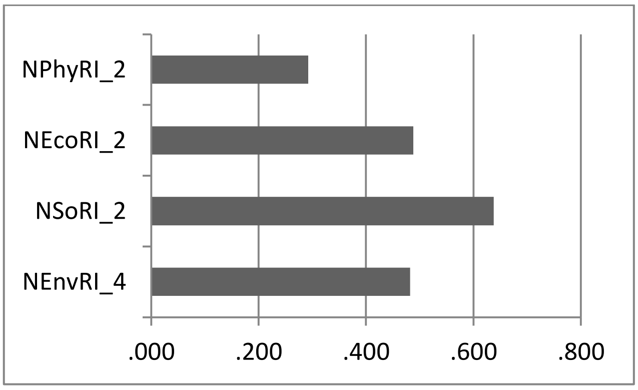


Figure 7.14. Sensitivity measures of Neighbourhood Disaster Resilience Index
*Standardised regression coefficients are significant ($p<0.01$,n=76, R^2=0.99)

Altering the aggregation scheme for calculating overall NDRI has a very moderate impact on the overall neighbourhoods' ranking by only 2 median rank changes. However, ninety percent of the neighbourhoods change their position by 5 or fewer ranks. It can be concluded that an average rank change of two positions is acceptable; and NDRI shows moderate sensitivity. The most extreme changes occur in Fairfield, Chelmer and Graceville with seven rank changes. This volatility is the result of the moderate compensatory logic in index design. In conclusion, the NDRI shows adequate construct validity. Its low sensitivity to different inputs to the index confirms that its structure and design is sound and indicators representation is balanced.

Table 7.10. Sensitivity analysis and correlation analysis findings applied to NDRI

	NDRI_ Linear	NDRI_ Geometric
Top five neighbourhoods	Moggill Anstead Kholo Barellan Point Bellbowrie	Moggill Anstead Kholo Barellan Point Jamboree Heights
Bottom five neighbourhoods	Rocklea West Ipswich Archerfield Riverview Churchill	Rocklea West Ipswich Archerfield Riverview Churchill
Median rank change		2
Range rank change		0-7
The most extreme change		Fairfield-Chelmer-Graceville
90th percentile rank changes		5

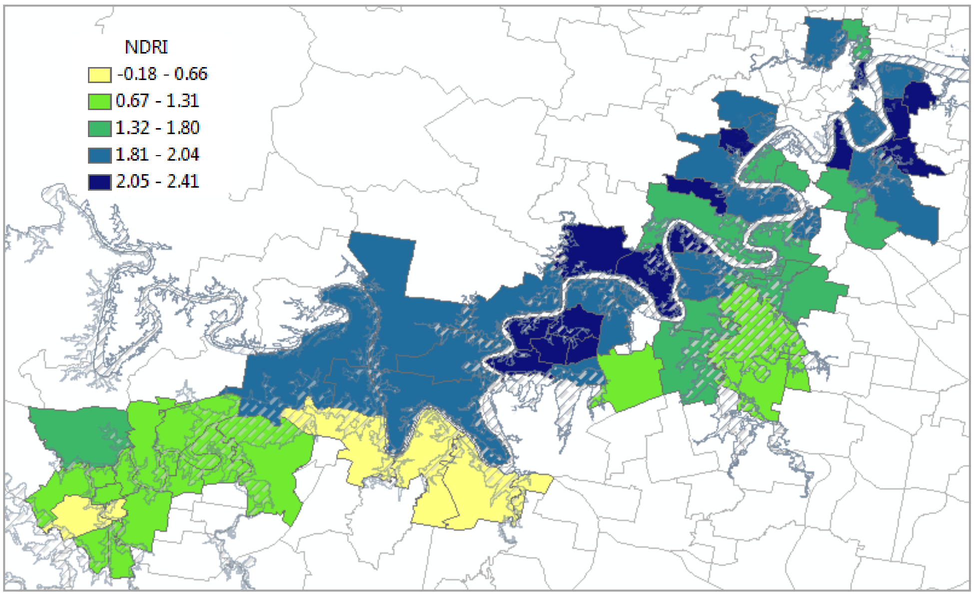


Figure 7.15. Spatial variation of Neighbourhood Disaster Resilience scores

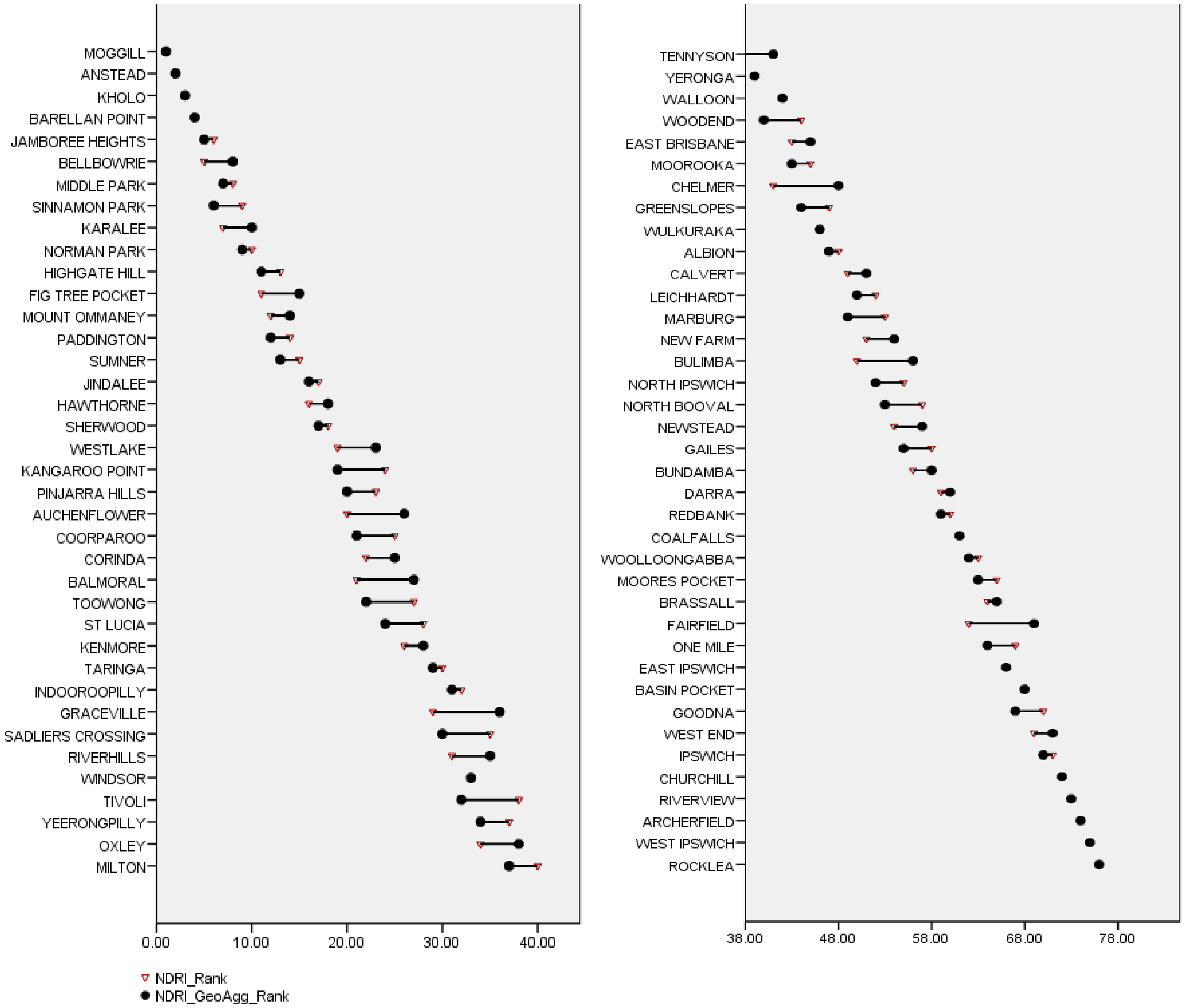


Figure 7.16. Alternative NDRI ranking

7.4. Summary

In this chapter the reliability of the proposed NDRI has been examined using inter-item correlation analysis for an individual reliability assessment, and stratified Cronbach alpha coefficients for a composite reliability assessment. Considering the multidimensional and formative nature of the NDRI, it does not assume high internal consistency between components. The results on the inter-item correlations show that the majority of the indicators within unidimensional sub-components of the model are statistically significant and positively correlated ($p < 0.05$, $p < 0.01$), which implies a high degree of consistency of these measures. Some variations exist in terms of magnitude and strength of correlations, but overall the correlation patterns are reasonable. In sum, the NDRI which is the composite scale of resilience exhibited an acceptable level of stratified Cronbach's alpha coefficients (0.580), suggests that it is a fairly reliable measure. On the other hand, the negatively and insignificantly related indicators have been dropped from the scale to improve parsimony. This resulted in a refined set of indicators which have been used to calculate the second alternatives for each component.

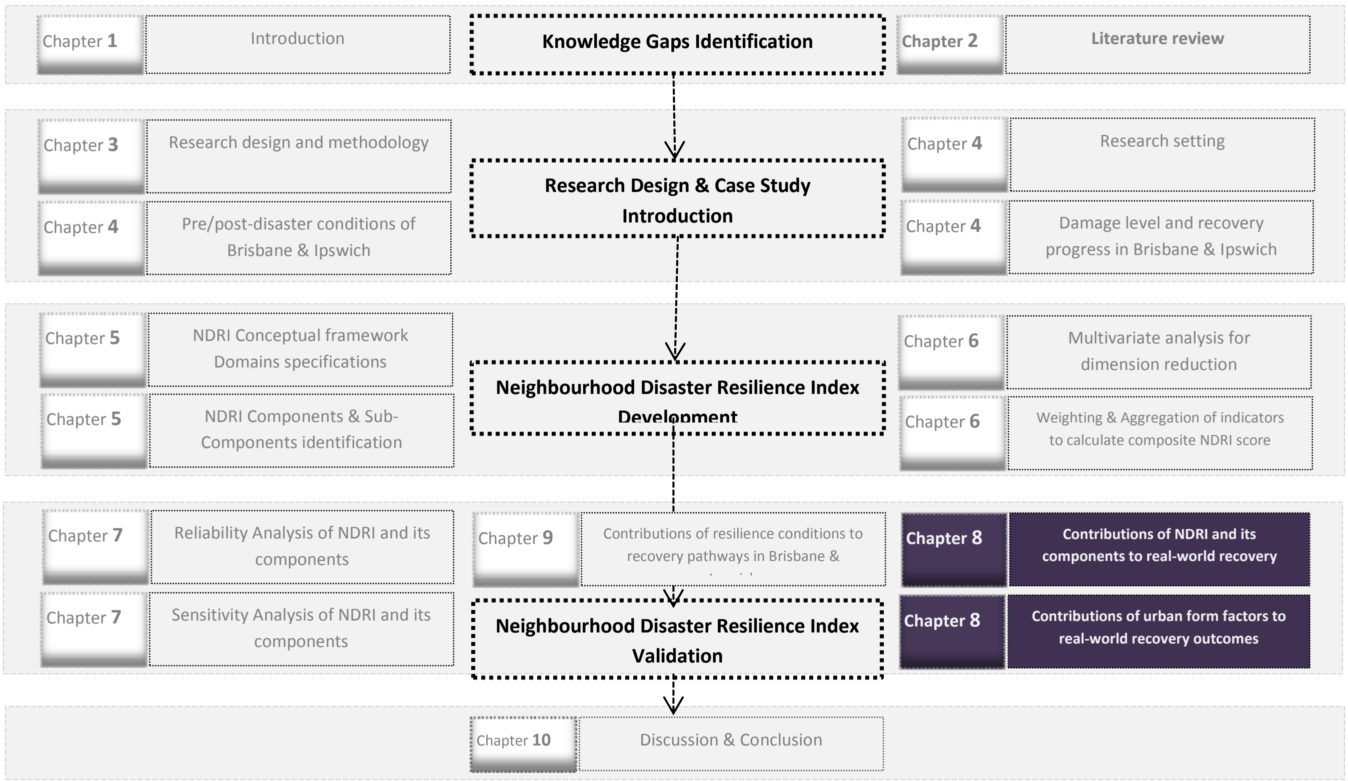
Assessing the robustness of the index using sensitivity and uncertainty analysis shows a relatively balanced representation of the indicators, and moderate methodological uncertainties. The exclusion of some indicators (Table 7.11) improved the robustness of the sub-indices in their second alternative. Other than these methodological uncertainties, many of the issues with robustness of the index originate from resilience concept epistemological issues, such as the interactions between resilience indicators and their outcomes. This is not identified thoroughly in the extant literature. However, parts of these uncertainties are investigated by contribution of these indicators to real world recovery outcomes in Chapter 8.

Table 7.11. List of indicators omitted after the sensitivity analysis

Resilience component	#indicators after MVA	#indicators after SA	Indicators omitted after sensitivity analysis
Social	12	9	▪ % residents living at the same address as 5 years ago ▪ % immigrants who arrived before 2009 ▪ % population with education higher than 8^{th} year
Economic	11	10	▪ the percentage of commercial land use in flood area
Physical	23	17	▪ % services land use ▪ % educational land use ▪ % units with vehicle access ▪ dwelling density ▪ Building Type Diversity ▪ Land Use Mix
Environmental	7	4	▪ % of pervious land in flood risk areas ▪ % residential land in flood risk areas ▪ % neighbourhood's land not in flood risk areas

Chapter 8
Index Validation

Contribution of NDRI and Its Indicators to Recovery Outcomes



8. Index Validation – Contribution of the NDRI and Its Indicators to Recovery Outcomes

8.1. Overview

In Chapter 7, the internal structure and robustness of the NDRI was assessed. Chapter 8 seeks to assess the external validity of the composite indicator, its components and sub-components. A complete and comprehensive validation of resilience models is not possible, since observational data are available only for parts of the modelling domain (Cullen & Frey, 1999). As a result, partial validity for the recovery outcomes is examined in this chapter.

Research questions

- To what extent is each indicator, sub-component and component of the NDRI contributing to recovery outcomes?
- To what extent are the urban form variables contributing to recovery outcomes?

Methodology

In this chapter the validity of NDRI and its components is assessed by examining the measures of its content, construct and criterion related validity. Carmines et al. (1979) argues that different dimensions of validity need different approaches. In this research, content validity was assessed in Chapter 4 by examining whether NDRI indicators captured all intended domains of the defined construct. In this chapter, construct validity is examined using correlation analysis to investigate the interrelationship between variables and the recovery outcomes as real-world empirical results of resilience. Furthermore, regression analyses are conducted to examine the ability of NDRI, its components and indicators, to predict the recovery outcomes which are referred to as the criterion-related validity. This is extended by investigating how NDRI adds incrementally to prediction of the recovery outcomes. Finally, as the relationship between NDRI, recovery outcomes and urban form indicators shows great potential as a physical indicator of resilience, a more detailed investigation of the contribution of urban form variables on recovery of the Brisbane and Ipswich neighbourhoods is conducted.

To conduct the statistical analyses, the data screening, verification of assumptions, model diagnostics and follow-up analyses are conducted in this chapter. There are various kinds of regression techniques used to make predictions. These techniques are driven by three metrics: the number of independent variables, the type of dependant variables and the shape of the regression line. In this chapter, to assess the validity of the NDRI, the best suited regression techniques are chosen, based on types of independent and dependant variables, dimensionality in the data and other essential characteristics of the data. The dependant variables in some cases are log-transformed or categorised and analysed using multivariate or logistic regression analysis.

The ordinal logistic models are developed under proportional odds assumption, and therefore to decide whether the model is correctly specified, goodness of fit (GOF) tests and sensitivity analysis are performed by fitting and comparing different models (Ananth & Kleinbaum, 1997). Deviance and Pearson are used as GOF statistics. If the p value produced by the GOF test is lower than 0.05, then the model is rejected and if it is higher than 0.05, then the model has passed the test (Allison, 2014).

As a final stage in regression analysis, the assumptions of the models are checked and confirmed. The collinearity is checked by the variance inflation factor, a diagnostic function in SPSS and the independency of residual is checked by Durbin-Watson.

8.2. Validity of Neighbourhood Disaster Resilience Index

The validity issue is often a misunderstood problem in resilience and vulnerability assessment literature (Sherrieb et al., 2010). Validity in this area is not an absolute measure; it is relative to the domains about which statements are made (Sireci, 2007). The comprehensive validity of resilience measures as a complex and multi-dimensional concept is challenging, as it is difficult to find empirical evidence of resilience. Moreover, the nature of indicators and indices as indirect numerical proxies of real phenomena makes it difficult to quantitatively assess a qualitative phenomenon. However as previously mentioned, partial validation of the index is conducted in this chapter using different methods. These validation tests can provide a basis for the collective judgments of persons familiar with this field to decide about the final acceptance of validity of the construct (Ranger & Kuhn, 2012).

Carmines et al. (1979) defines three types of validity: content, construct and criterion. These three validation types incorporate nearly all forms of validity that have been suggested in the related literature on vulnerability and resilience assessment tools (Bryant, 2000; Fekete, 2009; Fornell et al., 1982; Füssel, 2010; Gall, 2007; Vincent, 2004). These methods are further elaborated on in the sections below.

8.2.1. Content Validity

Content validity depends on whether the content positively and thoroughly defines the dimensions of the construct and its measures (Carmines & Zeller, 1979). For content validity assessment, it should be checked that the content of the construct adequately represent the domains they are meant to measure. In this study, content validity has been the guiding principle of development of the construct from the beginning. Indeed the theoretical framework, construct specifications and cross-classification matrix in Chapters 3 and 4 guided the selection of the content. The indicators of impact level and the capacity to respond and recover quickly for each dimension are extracted based on the guiding matrix, which could guarantee that it covers the full range of dimensions associated with neighbourhood disaster resilience intended in this study.

8.2.2. Construct Validity

Construct validity has evolved since mid-1950 when social scientists concluded that no clear criteria existed for most of the social measures/constructs being developed (Sireci, 2007). Therefore, for the assessment of the construct validity, more explicit foundations were established by positively specifying the dimensions of the construct, the domain of the dimensions, and the expected relations of the dimensions to each other. Discriminant evidence in construct validity normally demonstrates that the proposed measure correlates better with a second closely related measure than it does with a distantly related measure (Babbie, 2013; Babbie & Rubin, 2008; Carmines & Zeller, 1979). However, considering that the NDRI is a formative construct, discriminant validity is not meaningful in this case. The convergent evidence can be the same as evidence that is used to argue for criterion validity. Instead of looking for a perfect correlation with the assumed criterion, what is sought here is only the direction and level of correlation between the proposed measure and a single existing measure. Convergent evidence is obtained either by showing that a test is related to other measures of the same phenomenon, or by observing empirical relationships that can be predicted from the theoretical description of the construct. Establishing convergent validity for the NDRI requires that it shows expected correlations, positive or negative, with other single variables presumed to be related to, or associated with, disaster resilience.

Construct validity in this research is assessed by examining the interrelationship between the NDRI and its components' scores with the following theoretically relevant measures:

(1) The level of property damage loss due to the 2010/2011 flood in Queensland. The data on property damage loss are obtained from DARMsys database, at the Queensland Reconstruction Authority;

(2) Recovery and reconstruction status of flood affected properties: This is calculated based on the changes in the damage level of each property. The data for this variable are obtained from the same database, DARMsys;

(3) Social vulnerability index (SoVI): This is an index developed by the Hazard Vulnerability Research Institute at the University of South Carolina, which is replicated for this study using Census data (Cutter et al., 2003; Tate, 2012); and

(4) Flood risk and exposure which is calculated based on the flood risk data obtained from the Queensland Government's online database. (The flood risk in this database is defined based on the Annual Exceedance Probability (AEP) and Average Recurrence Interval (ARI))

Table 8.1 presents the results of correlation (correlation of zero-order) analysis between NDRI, its indicators and the external criteria. In this table, 'PerRec10' shows the percentage of properties reconstructed in 10 months after the flood and 'DL0711' indicates the total Damage Loss in 07.2011

Table 8.1. Bivariate correlations between external criteria, NDRI and its components

	PerRec10	PerRec13	PerRec16	DL0711	SoVI	BrisIps	Risk
NDRI	.364**	.378**	.272**	-.053	-.465**	.676**	-.444**
NSoRI	.220*	.270**	.179	.124	-.544**	.708**	-.586**
NEcoRI	.448**	.429**	.324**	.053	-.418**	.726**	-.601**
NEnvRI	-.215*	-.195*	-.055	-.413**	.417**	-.695**	.868**
NPhyRI	.473**	.510**	.290**	.006	-.212*	.729**	-.547**
Not vulnerable pop	.266**	.289**	.184	-.002	-.409**	.654**	-.484**
Participation	.134	.210*	.178	.177	-.498**	.602**	-.485**
Access to resources	.291**	.283**	.227**	.035	-.578**	.491**	-.459**
Human capital	.335**	.371**	.230*	.037	-.439**	.838**	-.689**
Economic stability	.430**	.404**	.307**	.047	-.386**	.652**	-.557**
Resource equity	.466**	.447**	.334**	.019	-.435**	.746**	-.598**
Risk exposure	-.204*	-.188	.013	-.297**	.489**	-.654**	.876**
Protection resources	-.057	-.112	-.157	-.122	-.069	-.126	.028
Physical exposure	.217*	.238*	.057	-.047	.012	.192*	-.061
Medical capacity	.209*	.148	.078	.091	.067	.104	-.150
Shelter capacity	.182	.290**	.215**	-.119	-.061	.187	-.194*
Transport capacity	-068	-.152	-.139	-.222*	-.238*	-.030	-.083
Communication capacity	.263*	.294*	.177	.076	-.529**	.653**	-.587**
Diversity redundancy	.276**	.326**	.150	.062	.164	.460**	-.237*
% Land not in flood area	-.255*	-.242*	-.058	-.281**	.418**	-.831**	1
% Res not in flood area(-)	-.243*	-.252*	-.053	-.335**	.421**	-.831**	.953**
River side km(-)	.212*	.169	.228*	-.108	.191*	.308**	-.171
% Wetland in flood area	-.113	-.021	-.023	.048	-.284**	.311**	-.307**
% Recreational land	.049	.113	.163	-.253**	-.054	.107	-.107
Non built-ip in flood area	.096	.132	.062	-.126	-.132	-.020	.076
Bld post 1981	-.074	-.082	-.166	-.006	-.095	-.015	.073
% Service in flood area(-)	-.171	-.149	-.125	.142	.192*	-.083	.199*
% Not single fam detached	.295**	.284**	.082	.070	.190*	.452**	-.337**
# hospital per 10,000	.209*	.148	.078	.091	.067	.104	-.150
# Schools per 10,000	.111	..162	.186	-.316**	-.059	.058	-.094
# Plac worship10,000	.204*	.191*	.176	-.192*	-.180	.191*	-.270**
# Police 10,000	-.079	-.157	-.024	-.046	.083	-.164	.153
# Fire 10,000	.021	.030	.075	-.091	-.041	.131	-.145
#SES 10,000	.010	-.004	.038	-.127	.034	.044	.018
Principle rd 10,000	-068	-.152	-.139	-.222*	-.238*	-.030	-.083
Dwl internet connection	.263*	.294*	.177	.076	-.529**	.653**	-.587**
Dwl density	.340**	.437**	.321**	.071	.179	.516**	-.281**
BTD	.191*	.219*	.067	.147	.282**	.412**	-.276**
Population age	.297**	.326**	.184	.017	-.065	.510**	-.367**
Not need assistance	.180	.239*	.185	.015	-.377**	.587**	-.474**
Not rent public house	.008	.073	.005	.026	-.534**	.401**	-.284**
Not single parent family	.440**	.375**	.218**	.020	-.496**	.728**	-.598**
Addrss 5 years	-.232*	-.312**	-.214*	-.030	-.279**	-.305**	.245*
Immigrated bf 2009	-.216*	-.325**	-.093	-.114	-.193*	-.618**	.455**
Owner occupied	-.148	-.199*	-.076	.030	-.621**	-.033	-.018
Volunteers	.120	.204*	.199*	.090	-.511**	.403**	-.318**
English sufficient	.031	-.097	.132	-.153	-.272**	-.416**	.330**
% Com service in fld zone	.103	.212*	-.073	.183	-.068	.204*	-.175
Employed	.407**	.453**	.328**	-.054	-.388**	.614**	-.508**
HHD income	.402**	.372**	.272**	.064	-.585**	.742**	-.655**
Female labour	.422**	.503**	.374**	-.069	-.259*	.606**	-.466**
House value	.422**	.422**	.263*	.055	-.395**	.789**	-.625**
Healthcare services	.264**	.267**	.263**	.067	-.035	.479**	-.309**
Financial services	.386**	.359**	.228*	.022	-.453**	.665**	-.569**
Employed in pr industry	.367**	.266**	.127	-.237*	-.557**	.299**	-.242*
Shopping centres	.034	.013	-.081	.113	.105	.049	.036
Economic resource _SEIFA	.342**	.344**	.220*	.062	-.588**	.726**	-.625**

*Significant p <05, **Significant p<01

Theoretically, it is expected that the more resilient neighbourhoods will suffer lower levels of property damage due to flooding compared to the less resilient neighbourhoods. However, in this case the negative association between NDRI and damage loss level is not statistically significant. This could be due to the fact that there are a number of neighbourhoods in the case study area which, despite their high risk exposure, have higher capacity for quick response and recovery. This could be attributed to the fact that these neighbourhoods are more likely to take protective measures to reduce flood damage. The NEnvRI has the strongest association with damage loss level ($r=-0.413$, $p<0.01$) as it takes into account all the risk and exposure measures. Most of the other resilience indicators are negatively associated with damage loss, including: % employed in primary industries ($r=-0.237$, p<05), principle roads km ($r=-0.222$, $p<.05$), # places of worship ($r=-0.192$, $p<.05$), # schools ($r=-0.316$, $p<.01$), % recreation land ($r=-0.253$, $p<.01$), % residential land not in flood area ($r=-0.335$, $p<.01$), % land not in flood area ($r=-0.281$, $p<.01$), transport capacity ($r=-0.222$,$p<.05$), risk exposure negative ($r=-0.297$, $p<.01$).

A disaster resilient neighbourhood is expected to recover and reconstruct the damaged properties more quickly compared to the less resilient neighbourhoods. This expectation is in line with the working definition of disaster resilience in this research (see Chapter 5) where there is an emphasis on the ability of the system to recover quickly by adopting resilience attributes, including robustness, resourcefulness, redundancy and rapidity. Considering these attributes in the development of the NDRI and its components, it is expected that a direct and positive relationship between recovery status and NDRI and its components will be seen, specifically NSoRI and NEcoRI, which are developed with a focus on resourcefulness measures.

As anticipated, the overall neighbourhood disaster resilience index is significantly and positively correlated with the recovery level after 10 months ($r=0.36$, $p<0.01$), recovery level after 13 months ($r=0.38$, $p<0.01$) and recovery level after 16 months ($r=0.27$, $p<0.01$). Among the NDRI components, NEcoRI ($r=0.45$, 0.43, 0.32, $p<0.01$) and NPhyRI ($r=0.47$, 0.51, 0.29, $p<0.01$ show the strongest positive correlation with recovery progress. The direction of correlations among all sub-components and recovery progress are positive, as anticipated, except for place attachment and risk exposure. Place attachment shows mixed behaviour. It has no significant correlation with damage level, while it shows significant negative correlation with recovery ($r=-0.22$,-0.29, -, $p<0.01$), with SoVI ($r=-0.48$, $p<0.01$) and with Brisbane Ipswich dummy variable ($r=-0.27$, $p<0.01$).

The NEnRI shows mixed impact on resilience as it has strong negative association with damage level, and also has a statistically significant negative correlation with recovery progress ($r= -0.22$,-0.19, - , $p<0.01$). This could be due to the fact that the neighbourhoods in flood risk zones could be more prepared and have more capacity to recover after the flood despite their higher flood exposure. These communities are more likely to have high perception of risk, considering that they have probably experienced floods before. This could be considered as a factor for neighbourhoods in taking disaster protective and preparedness measures and hazard alterations. Also, frequent experiences of flood could have resulted in developing better disaster preparedness programs. Former studies suggested that experience is an important factor in higher level of disaster preparedness and response, as it leads to greater awareness of consequences (Mileti, 1999). Therefore, it is expected that the frequency and extent of risk could have mixed effects on different aspects of disaster resilience. While it contributes to higher exposure and damage, it could also contribute to more effective response and recovery.

Among the individual indicators of resilience, economic factors have the strongest correlation with recovery progress including % employed population ($r=.41, .45, .33$ $p<0.01$), HHD income ($r= .40, .37, 27$, $p<0.01$), % female labour force ($r= .42, .50, .37$, $p<0.01$) and some other social and physical resilience indicators. As stated before, most of the environmental resilience indicators have mixed relationships with resilience, contributing to both damage and recovery at the same time.

As discussed in Chapter 2, several studies have theoretically considered the concept of social vulnerability and resilience in opposition (Eraydin & Taşan-Kok, 2013; Gilbert, 2010). Therefore, it is expected that a negative relationship between social vulnerability and NDRI and its components' scores will be observed. This is expected, as disaster resilience attributes and activities such as hazard mitigation and preparedness programs are likely to decrease social vulnerability (Dalziell & McManus, 2004; Gallopín, 2006). As anticipated, the social vulnerability index is negatively correlated with most of the resilience indicators, with the exception of the NEnvRI and risk exposure factors (this mixed behaviour was discussed previously). These results comply with the hypothesis that the more resilient neighbourhoods are more likely to have a low level of social vulnerability.

Lastly, regarding local governments; as expected, the results indicate that the dummy variable of neighbourhoods located in the Brisbane local government area is positively and strongly correlated with the NDRI, its components and also with most of the individual resilience indicators. This result shows that neighbourhoods in the Brisbane local government area are more likely to have a high level of disaster resilience compared to those located in the Ipswich local government area. Table 8.1 shows the complete correlation matrix between the NDRI and resilience proxies used for validation. Overall, these results suggest that the NDRI has construct validity.

8.2.3. Criterion Related Validity

The proposed measure, the NDRI, could attain criterion validity to the extent that it matches other observations that measure the proxies of resilience (including less damage, quick recovery and response). In this section, predictive validity is analysed by examining the contribution of the NDRI, its components, sub-components and individual resilience indicators to resilience proxies, including damage level and recovery progress within 10/13 and 16 months after the flood.

Contribution of Resilience Factors to Recovery

A set of regression models is calibrated in this section to find indicators contributing directly to the recovery and damage level of neighbourhoods. These indicators will then be used in Chapter 8 for the comparative analysis of disaster resilience and the pathways to recovery in the flood-affected neighbourhoods. A total of 20 regression models are calibrated, in which the dependant variables of these models are the percentage of properties which have been reconstructed after 10/13/16 months after the flood. The indicators of each resilience component are the independent variables in these models.

$$Y_n = \beta \ +\beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

Y_1 = Percentage of affected properties reconstructed after 10 months

Y_2 = Percentage of affected properties reconstructed after 13 months

Y_3 = Percentage of affected properties reconstructed after 16 months

Y_4 = RecIndex

Y_5 = Damage loss

X = Social/economic/environment/physical components indicators

β_0 = Y-intercept

β_v = Regression coefficients

ε = Error component

As a starting point, the assumptions of the multivariate regression model are tested for each fitted model to have a general view of relationships between variables and to facilitate the assessment of the variables, data patterns, and choosing a suitable model (Fox, 2000). The assumptions of multivariate regression including linearity, homoscedasticity, multi-collinearity and normality of the regression residuals are tested in this section. To analyse these regression results, the regression residuals are saved and the normality assumption on these residuals is checked by using 'normal quantile plots'. The residuals exhibit significant non-normalities, which indicate that P-values might be misleading, as they are based on the assumption of normally distributed residuals (Neter et al., 1990). To check the independence assumption, the Durbin-Watson test is used, which reveals the level of autocorrelation. The homoscedasticity is checked by visual inspection of the residual scatter plots. Some non-linearity trends are evident in residuals' plots against each independent variable.

Due to the violations of assumptions in most cases, log-transformation as a variance-stabilizing transformation is used for the dependent variables to reduce or remove the effects of heteroscedasticity, non-normality, non-linearity, and autocorrelation. However, to prevent the loss of data due to undefined values generated by taking the logarithm of zero, all the values are summed up with 1 before taking the logarithm. The analytical process is conducted again with transformed dependant variables. In this round, four models in which RecIndex is the dependant variable met all the required assumptions. Therefore, the multivariate regression results are valid for these models. However, all other dependant variables, including recovery outcomes and damage loss, are converted to categorical/ordinal variables, considering the nature of data pattern for recovery variables, and knowing the actual theoretical relationships between recovery outcomes and independent variables. This facilitates calibration of non-linear regressions for these models which do not need to meet those assumptions. To categorise recovery outcome variables, each neighbourhood is technically coded to differentiate between recovery categories where: a value of 1 represents all neighbourhoods in Stage I recovery (average recovery scores <25), 2 represents all suburbs in Stage II recovery (scores >=25 and <50), 3 represents all suburbs in Stage III reconstruction (scores >=50 and <75), 4 represents all neighbourhoods in Stage IV reconstruction (scores >=75 and <100), and a value of 5 represents all neighbourhoods that have fully recovered (average recovery scores = 100). Damage loss is categorised using natural break classification to covert damage level to 5 categories.

Ordinal logistic regression is used to calibrate models in which recovery outcome is the response variable, as it is deemed more appropriate to fit these categorical dependent variables. Ordinal logistic regression applies maximum likelihood estimation after transforming the dependent variable into a logit variable. Furthermore, Poisson regression models are used to identify independent variables associated with the damage level. The Poisson regression is chosen as the response variable (damage loss) inclined mostly on category 1 damage. In contrary to fitting a straight line to these data, in Poisson regression a Poisson distribution is applied to estimate the maximum likelihood from response value.

Table 8.2. Regression models results of selected resilience variables and recovery outcomes

Disaster resilience variables	%Rec10 Ordinal Logistic	%Rec13 Ordinal Logistic	%Rec16 Ordinal Logistic	Damage Loss Poisson Regression	ResIndex_log Multiple Regression
Model's goodness of fit_R^2	Nagelkerke =0.27	Nagelkerke =0.28	Nagelkerke =0.17	Deviance =0.613	-
HomeOwner	-	4.89**	-	-	-
% Volunteers	.054*	.068*	-	4.92*	
Human capital- SEIFA	13.76**	9.59**	3.37*	-	-
Model's goodness of fit	Nagelkerke =.46	Nagelkerke =.22	Nagelkerke =.33	-	-
Income level	.405**	4.61**	.06**	-	-
% Employed not in primary industries	10.39**	-	-		-
Model's goodness of fit	Nagelkerke =0.259	Nagelkerke =0.282	Nagelkerke =0.133	-	-
%DWIC	3.33*	5.20**	3.39**	-	-
Service land 10,000	6.05*	8.53**	5.27**	-	-
Non single family detached houses	5.73**	4.39**	-	-	-
Model's goodness of fit	Nagelkerke =0.10	Nagelkerke =0.22	Nagelkerke =0.23	Deviance =0.435	R_Square =.172
%Residential in flood risk area(-)	5.9*	.23	5.9*	.312**	.415**

* Significant at 0.05
** Significant at 0.01

Table 8.2 demonstrates the results of the regression analysis for resilience indicators. All models present a good fit, the test of parallel line does not reject the null hypothesis ($p > 0.05$) and the Pearson chi-square goodness-of-fit measure is always non-significant. These summary measures suggest satisfactory ordinal logistic regression models. Only statistically significant results are reported here due to the large size of the output tables. The parameter estimates denoted by B in Table 8.3 relates the recovery progress to resilience variables selected in NDRI. Exp (b) refers to an odds ratio which is the natural log base of the parameter estimate. An Exp(b)>1 suggests that the independent variable increases the odds of recovery progress to the next level. For example, the results suggest that for every percentage increase in non-minority residents during the first year of reconstruction, communities have about 13 odds of being in a higher recovery progress category 10 months after the flood. These odds decrease over time, to 9 odds for recovery after 13 months and 3 odds for the recovery progress after 16 months. These parameters provide the means to identify the variables with strong and significant predictive power.

The pseudo R-square statistics for the ordinal logistic models ranges from 0.133 to 0.462. The range of explanatory power for the individual resilience variables is low. However, it should be recognized that these variables are only part of the components which are hypothesised to affect resilience. Moreover, the proxies selected to represent and validate the NDRI are not covering all aspects of the definition of NDRI. The proxies in this section are limited to the affected residential properties and therefore could not represent all aspects of the NDRI. For example, some resilience variables have an impact on the disaster response phase (such as the capacity to provide temporary shelter and medical facilities) rather than disaster recovery and reconstruction. Therefore, the calibrated models for reconstruction status and these variables show relatively low R^2 statistics, and even in some cases show negative B parameters in contribution of resilience variables to reconstruction progress (such as number of volunteers, which is positively associated with damage and negatively associated with the recovery progress).

The results reveal that twelve of the forty-five indicators are directly and strongly contributing to resilience proxies (statistically significant $P<0.05$) as shown in Table 8.2. Social component models have three predictors with human capital and number of volunteers contributing significantly to all resilience proxies. The explanatory power of the economic resilience subcomponent are the highest ranging from R-square = 0.22 to 0.462. Two economic resilience variables, income level and employment in primary industries, are found to be strong predictors of resilience proxies, based on their statistical significance. Physical component shows three predicting indicators, including the percentage of dwellings with internet connection, percentage of non-single family detached houses and percentage of land used for services. The only statistically significant predictor ($p<0.05$) of resilience proxies in the environment component is the percentage of residential land not in a flood risk area. In fact, these variables show the extent to which the neighbourhood community has adequate assets and resources to recover quickly after the flood. The 'percentage of population employed' only contributes to recovery after 16 months. This can be attributed to the situations where just having economic resources due to employment does not facilitate quick recovery in the first months after the flood, and other factors may contribute more to recovery in the short term.

Contribution of Neighbourhood Disaster Resilience Sub-components to Recovery Outcomes

A binary logistic regression is used in this section to further understand contributions of the four resilience components and sub-components to disaster recovery outcome in the Brisbane and Ipswich neighbourhoods after the 2011 flood (Table 8.3). For this purpose, the recovery outcome was coded to fully recovered (=100) and not fully recovered (<100). The models were calibrated for three time points of the flood recovery and the parameter estimates are shown in Table 8.3. The explanatory powers of these models are moderately low (adjusted R^2= 0.11 to 0.32) which could be explained with reference to other post-disaster influential factors such as successful insurance claims, governmental recovery funds (federal, state and local) (Irajifar et al., 2015). Most of the components and sub-components achieved some degree of statistical significance (<0.05) at least at one of the recovery points, with the exception of medical capacity and shelter capacity in the physical component. This non-contributory behaviour of these sub-components to some extent was predictable, since the indicators in these sub-components were selected based on their contribution to the response capacity and not for their reconstruction capacity.

The results show that economic stability is the strongest predictor of recovery within 10, 13 and 16 months after the flood. After the economic component, social sub-components are the main contributors to post-flood recovery. The differences in recovery progress among neighbourhoods are distinguishable by economic stability. For example, neighbourhoods such as New Farm and Paddington, with high levels of economic stability, recovered quickly after the flood although they sustained high levels of flood damage, whereas in neighbourhoods with low economic stability such as Goodna and Archerfield, the reconstruction progress was much slower. This can be attributed to their financial resources and also the probability of having adequate flood insurance. Moreover, environment sub-components also show statistically significant negative relationships with full recovery by determining the extent of damage sustained in each neighbourhood, as it includes the hazard exposure and frequency variables.

In addition to the association of social, economic and environment components with full recovery, the effect of institutional factors was examined by defining a dummy variable for the neighbourhoods located in each of the Brisbane and Ipswich local government areas. The regression model shows a low R^2 statistics (=.08), however the variable has a statistically significant association with recovery at all three time points after the recovery (Table 8.3).

Table 8.3. Model results for the resilience sub-components and recovery outcomes

	%Reconstructed10		%Reconstructed13		%Reconstructed16	
	B	sig	B	sig	B	sig
NEnRI	-1.8	.08	-1.8	.02*	-1.9	.015*
Risk and exposure	-.21	.06	-.23	.04*	-.13	.24
Protection resources	-.26	.02*	-.34	.003*	-.23	.04*
Hazard frequency	-.20	.08	-.16	.07	-.42	.000***
NEcRI	.29	.01*	.49	.000***	.31	.007*
Asset xxposure	-	-	.28	.014*	-	-
Economic stability	.34	.003**	.46	.000***	.47	.000***
Resource equity	-	-	.20	.08	.37	.001***
NPhRI	-	-	-.23	.04*	-.27	.02*
Physical exposure	-.35	.002*	-.34	.003**	-.13	.26
Response capacity		-	-.23	.04*	-	-
Transportation capacity	.22	.05*	.26	.03*	.16	.15
Urban built form	.24	.04*	.25	.03*	-	-
NSoRI	.27	.20	.34	.003*	.39	.000***
Not vulnerable population	.18	.129	.27	.02*	.37	.001***
Participation	.10	.39	.24	.04*	.41	.000***
Access to resources	-	-	-	-	.31	.006**
Human capital	.29	.01*	.37	.001**	.38	.001***
NDRI	.35	.002*	.43	.000***	.49	.000***
Damage loss	-	-	-	-	.23	.04*
Brisbane/ Ipswich dummy	.31	.006*	.44	.000***	.29	.01*

*Significant at 0.05
**Significant at 0.01
***Significant at 0.001

The results suggest that the amount of damage sustained is the strongest predictor of recovery for all respective years; β = -.872 for one year, β = -.637 two years, β = -.469 three-years, β = -.313 four years, and β = -.355 for five years following the event. However, following damages sustained, the recovery process along the coast is to a large extent determined by social and economic factors of disaster resilience. In the first year, economic resilience comprised the second largest predictor (β = .602) followed by the social resilience parameter (β = .555). Social vulnerability, as defined by the Social Vulnerability Index, is the fourth largest predictor (β = -.467). The statistical significance of the Social Vulnerability Index is noteworthy since the statistical association between the SoVI and the differential recovery occurring along the Mississippi coast suggests that indicators of social vulnerability may be utilized as predictors of recovery, and some researchers argue that in order to measure resilience, attention must be given to a population's social vulnerability (Tobin & Whiteford, 2002). However, when compared to the predictive strength of the subcomponents of social and economic resilience over time, the predictive strength of the association between the SoVI and the recovery outcome along the coast decreases markedly.

Contribution of Neighbourhood Disaster Resilience Index to Recovery Outcomes

In this section, the ability of the NDRI to incrementally add to predicting recovery outcomes over alternative measures is assessed. To better understand the extent of the contribution of the resilience index to flood recovery outcomes in the Brisbane and Ipswich neighbourhoods, a series of modelling procedures are developed to relate the disaster recovery outcomes to NDRI, SoVI and Damage Loss.

$$ln\ (\gamma_n) = \beta_0 + \beta_1 NDRI + \beta_2 SoVI + \beta_3 Damage\ Loss + \varepsilon$$

In the previous section, the ability of the NDRI to predict recovery outcomes was assessed while controlling for the SoVI. It was revealed that the NDRI performs well relative to the SoVI, a similar measure for vulnerability and resilience measurement. The NDRI performs as expected while the SoVI occasionally yields insignificant results which sometimes are against the theoretical expectations. In this section, the incremental validity of the NDRI is assessed with respect to the SoVi and damage loss. This would answer the argument that the NDRI could be parsimoniously measured by damage loss and the SoVI. Therefore, in this model, damage loss and the SoVI are entered first and then the NDRI is entered to see if it contributes to prediction of recovery outcomes while controlling for the SoVI and damage loss.

For this purpose, the zero order correlations between the independent and dependent variables presented are assessed in Table 8.4.

Table 8.4. Correlation between variables used for incremental validity assessment

	NDRI	SoVI	DL0711_S	PerRec10	PerRec13	PerRec16	ResIndex
NDRI	1.000	-.465**	-.053	.364**	.378**	.272**	.117
SoVI	-.465**	1.000	.075	-.155	.018	-.070	-.088
DL0711_S	-.053	.075	1.000	-.291**	-.310**	-.516**	-.984**
PerRec10	.364**	-.155	-.291**	1.000	.775**	.581**	.428**
PerRec13	.378**	.018	-.310**	.775**	1.000	.719**	.421**
PerRec16	.272**	-.070	-.516**	.581**	.719**	1.000	.592**
ResIndex_S_Neg	.117	-.088	-.984**	.428**	.421**	.592**	1.000

*Significant at 0.05, **Significant at 0.01, ***Significant at 0.001

These inter-correlations suggest that there is significant negative correlation between the SoVI and the NDRI (-.465**), while it has no statistically significant correlation with recovery outcomes and damage loss. Damage loss has a strong negative correlation with recovery outcomes which increases over time. This correlation matrix shows that the NDRI performs better than the SoVI and almost as well as the damage loss. In the next section, whether the NDRI still performs well when controlling for the other variables in regression analysis is checked.

Table 8.5. Regression models predicting recovery outcomes by damage loss, SoVI and NDRI

	PerRec10		PerRec13		PerRec16		ResIndex	
	R2	B	R2	B	R2	B	R2	B
Damage loss	.114	-.118	.112	-.037	.113	-.113	.932	-.965***
Damage loss	.127	-.114	.114	-.041	.114	-.114	.932	-.964***
SoVI		-.113		.114		.027		-.026
Damage loss	.187	-.099	.227	-.016	.211	-.090	.938	-.960***
SoVI		.011		.316**		.022**		.008
NDRI		.310**		.505**		.489***		.086

*Significant at 0.05, **Significant at 0.01, ***Significant at 0.001

It is expected that the NDRI has a positive effect on recovery outcomes while the SoVI and damage loss have a negative effect. The first model regresses recovery outcomes on the control variable, damage loss. The second model then adds the SoVI and the third model includes the NDRI as well. The t-test is used to determine whether the new variable in each model adds incrementally to the previous model. The t-test is deemed an appropriate method, as a single variable is added in models 2 and 3. The first model, which includes only damage loss, accounts for 11% of the variance with no significant contributors. The second model has a relatively higher R_square of 13% and the SoVI is not significant but it is in the anticipated direction. The third model has a higher R2 of 19% and the NDRI and the SoVI are both significant and in the anticipated direction. Moreover, the significance t-test for the NDRI shows that it actually contributes to the recovery outcomes even with the inclusion of the SoVI and damage loss that remains non-significant. The results for the models predicting recovery outcomes within 13 and 16 months after the flood also support the NDRI's incremental validity (Table8.5).

Overall, the results of this section reveal that the NDRI contributes to the prediction recovery outcomes which could not have been attained by the SoVI or damage loss alone. This suggests that the NDRI, as a new index, makes a valuable contribution to the hazard literature and has the potential to greatly help planners and emergency managers.

8.3. Contribution of Urban Form Indicators to Disaster Recovery Outcomes

In this section, the contribution of urban form variables to recovery outcomes is investigated and non-urban form factors are used as control variables. Population density, land use mix and building type diversity are considered as urban form factors that contribute to the resilience attributes discussed in Chapter2. Income, single parent families and home ownership are also considered as non-urban form contributors of resilience - as already established in the literature (Ahern et al., 2006; Birkmann, 2006; Cutter et al., 2003). A multiple regression and correlational research design is used in which the relationship between urban form as independent variable and the recovery outcome as dependent variable is analysed. Although longitudinal data of reconstruction progress after the flood is being used to detect the neighbourhoods' recovery status, the research design is cross-sectional and does not have the ability to document causality. Below, a brief background of the relationship between urban form and resilience is discussed, followed by the aforementioned analyses (Carpenter, 2015).

8.3.1. Background

The literature on disaster recovery planning refers to the urban environment as a place that should be recovered, rather than the one that could support recovery after disasters (Allan et al., 2013; Norman, 2006). The built environment's role in the mitigation phase of disaster management has been addressed in the literature (Carpenter, 2015; Haigh & Amaratunga, 2010), but not enough attention has been paid to the role of built environment characteristics in the recovery phase. This overemphasis on robustness and mitigation could lead to rigidity and fragility. Resilience shifts the focus of disaster management from merely a mitigation perspective to adaptation in response and recovery (Kärrholm et al., 2014; Müller, 2011).

There are some indications in the literature on the effects of urban form factors, such as discussions on the role of density and land use mix in disaster resilience (Allan et al., 2013; Berke et al., 2009; Carpenter et al., 2001; Godschalk, 2003). Allan et al. (2013), for example, investigated the role of urban morphology on the recovery process after earthquakes, and suggested that integrating resilience attributes into design and development strategies increases the capacity of urban areas in response to, and recovery from, disasters.

Very few studies have utilised time series data to examine and contextualize the recovery of neighbourhoods after disasters. Carpenter et al. (2013b) exploited the return of occupied housing units as a proxy for examining the recovery of neighbourhoods after Hurricane Katrina on the Gulf Coast, USA. They suggest that at suburb level, certain characteristics of the built environment, such as land use diversity and density, influence and support social capital and place attachment, which then facilitate disaster resilience and recovery. Chang et al. (2010) utilised different statistical indicators as proxies of recovery, namely population return and economic recovery, by a temporary boost in the reconstruction activities. They analysed the recovery of Kobe, Japan, following the earthquake of 1995, by the time of regaining the 'new normality' for each indicator. The recovery proxies used in their study (Change et al., 2010) are unique in terms of scale and unit of analysis, and also the precise time series reconstruction status data collected after the disaster.

The Resilience Alliance (2012) defined resilience as the capacity of a system to absorb the shock and to sustain and develop its fundamental function, structure, identity and feedback through recovery or reorganisation in a new context. According to this definition, two components should be considered when investigating disaster management in the built environment. The first is the resistance of the urban system, which is more related to the preparedness and mitigation phases of the disaster management cycle. The second is the coping capacity of an urban system for response and recovery after a disaster. In fact urban resilience is a function of the resistance and coping capacity of individual components of urban systems and the networks that binds them together. A resilience strategy needs then involve the avoidance of hazardous areas and the addition of resilient characteristics (robustness, diversity, redundancy, resourcefulness and collaborative capacities) for those components that remain vulnerable (Irajifar et al., 2013; Little, 2003). So, unlike the concept of disaster resistance which is more focused on preparedness and mitigation, the concept of coping capacity emphasizes the response and recovery capacity of urban systems to cope with the particular challenges of various natural disasters.

Disaster mitigation and recovery create a 'density conundrum' in the context of urban planning. On one hand, compact development can specifically direct land uses, infrastructure systems and socioeconomic activities to non-hazardous areas and also facilitate improved access to resources, services and amenities by bringing in diversity (Chang & Shinozuka, 2004; Lall & Deichmann, 2012). On the other hand, high densities inherently pose a variety of risks: fire, building collapse and violence. It can result in a loss of permeable surface and can also increase the exposure of people and assets, particularly where poor quality and ill-maintained infrastructure and low-quality buildings come into play. However, zoning ordinances can reduce exposure by limiting the development or the density of human occupancy in particularly hazardous areas, by creating or maintaining open spaces, and by limiting the placement of critical facilities such as hospitals, power plants and schools (Godschalk et al., 1998). Thus, the answer to this density conundrum in the context of disaster resilience is argued to be an urban form that allows communities to minimize these contradictory aspects. The findings from the literature suggest that resilient cities need to embrace diversity, density, mix of uses, users, building types and public spaces (Allan & Bryant, 2011b; Jha et al., 2013).

Table 8.6 shows a number of links discussed in the literature on how different tools of land use planning including locational, structural, operational and fiscal tools can contribute to the resilience attributes of an urban system, such as robustness, redundancy, resourcefulness and rapidity.

Building upon threads of links between resilience attributes (a collaborative and engaged community, social networks, efficiency, and redundancy) and the built environment in the literature, this section seeks to empirically determine whether a link could be established between a denser and varied built environment and resilience.

Two factors should be taken into account in investigating the contribution of the built environment factors to disaster recovery. The first factor refers to the different contexts of urban systems that are being investigated in different studies. In an urbanizing developing world, the uncontrolled growth of population and economic assets in cities could potentially lead to an increasing concentration of hazard risks in urban areas, while in the developed countries it may lead to greater wealth and thus better coping capacity. Therefore, built environment factors should be considered in conjunction with other variables such as income and education. The second factor refers to the differences between general resilience versus specified resilience. This section investigates the recovery of the housing sector in a flood specific context.

Table 8.6. Linkage between land use planning and urban resilience attributes

		Land use indicators	Land use indicators description	Reference
Resistance (Mitigation and preparedness)	Exposure/ Avoidance	Open space preservation	Specific areas used for low intensity use to minimize property damage	(Godschalk, 1999); (Haigh & Amaratunga, 2010) (Berke & Smith, 2009)
		Zoning ordinance	Identifying and avoiding hazardous areas	
		Site selection and development controls	Keeping inappropriate land use and development out of hazard areas	
		Relocation	Mandatory or voluntary relocation of affected families to safe areas	
		Land acquisition	Purchase by government of land in hazard areas and provide alternative locations	
	Robustness	Design and building regulations	Application of appropriate building controls	(Stevenson et al., 2010) (Eraydin & Taşan-Kok, 2013)
		Strengthening and retrofitting of existing buildings	Reinforcing existing buildings and structures in hazard areas	
		Protection for lifelines	Critical facilities are ensured of their functionality during disasters	
Coping Capacity (Response and Recovery)	Redund ancy	Having redundant and back up critical buildings, such as hospitals, in the right places	The number of schools/ universities The number of hospitals/ clinics The number of power supply centres in the suburb	(Allan & Bryant, 2011b)
	Diversity	Diversity and land use mix can ensure the presence of different land uses in a specific area and thus it can have more resources and skills for response & restoration activities	LUM (land use mix) Proportion of land allocated to different land uses (percent of land uses) % of activities based on knowledge % of places dedicated to firms and businesses	(Allan et al., 2013; Salat et al., 2010a) (Carpenter et al., 2001)
	Resourcefulnes s	Financial incentives Access to resources in high density areas is better	Schemes for risk sharing through tax incentives	(Burby et al., 2000; Lall & Deichmann, 2012)
	Collaborative and feedback sensitive	Density increases social capital by tightening feedbacks More equitable form	Gross density (city/neighbourhood/suburb) Building block coverage Floor area ratio (city/neighbourhood/ suburb) Distribution (high density, low socio economic housing)	(Alessa et al., 2009; Allan & Bryant, 2011b; Jenks & Jones, 2009; March et al., 2011; Stevens et al., 2010)

8.3.2. Hypothetical Relationships

Based on the discussions in the background section (page 159), three hypothetical relationships have been analysed:

- That urban form (population density, building type diversity, and land-use mix) is related to disaster resilience;
- That urban form is related to disaster resilience when non-urban form factors are controlled for; and

• That the relationship between population density, building type diversity, land-use mix and disaster resilience is nonlinear.

The methods used to test the hypotheses are based on the nature of the hypothetical relationship. Tests of presence, strength, and direction of the linear relationship between urban form variables and disaster resilience proxies are conducted with the use of the Spearman correlation analysis. Hypotheses one and two seem similar, but in fact, in the second hypothesis the existence of the relationship is being investigated when other already established factors of resilience are controlled for. Multivariate regressions are conducted to test the second hypothesis, and cross-tabulation simulated the nonlinear relationships between urban form and disaster resilience variables.

8.3.3. Development of a Data Base for Hypothesis Testing

The data used for this analysis are obtained from a variety of sources. The variables used fall into three categories - disaster resilience, urban form and non-urban form. The data for disaster resilience proxies, the Damage Assessment and Reconstruction Monitoring system (DARMsys), have been obtained from the Reconstruction Authority of Queensland. The DARMsys is based on a comprehensive three monthly monitoring of reconstruction progress after the flood in Queensland. The data for other variables have been obtained from the Australian Bureau of Statistics, Queensland Government's online database, the National Exposure Information System and Risk Frontiers. A definition of the variables that are found to be most significant in the statistical analysis and the descriptive statistics for them is presented below.

Disaster Resilience: Dependent Variables

Two sets of proxies for disaster resilience are used based on the available data from comprehensive monitoring of reconstruction status after the 2011 flood in Queensland (DARMsys). These two sets of proxies are damage loss and reconstruction status. In this dataset, damage loss has been assessed based on the average monetary loss and categorised into four levels of property damage. 'minor damaged' properties are habitable but minor repairs are required (e.g. broken tiles on roof, windows damaged), while roughly 25%-49% of property is damaged in the 'moderately damaged' category, and the occupants may need to vacate while repairs are completed. About 50% or more of property is damaged in the 'severely damaged' category, and the property is not habitable. In 'totally damaged' properties, roughly 100% of the property is damaged and it is unlikely that the structure could be feasibly economically repaired. Considering these definitions of the damage data, the aggregated damage loss is calculated via the formula below:

Damage loss= (#minor damaged properties+ (25)* #moderately damaged properties+ (50)*#severely damaged properties+ (100)*#totally damaged properties)

Two alternative proxies have been considered for the reconstruction status. The first proxy is based on the level of change in the aggregated damage loss. As the reconstruction monitoring audits were conducted every three months after the flood for four rounds, the percentage of recovery is calculated within 10, 13 and 16 months after the flood, based on the formula below:

% recovery after 13 months = (damage loss 201107- damage loss 201205)*100/damage loss 201202

Moreover, the progress of reconstruction on properties with different levels of damage has been investigated in this study. These proxies are represented by the percentage of minor, moderately and severely damaged properties reconstructed during 10, 13 and 16 months after the flood. Dependant variables are presented in the first row of Table 7.7.

Urban Form: Independent variables

In the literature, density and diversity have been considered as attributes of disaster resilient urban systems (Allan & Bryant, 2014; Lall & Deichmann, 2011; Resilient Design Principles, 2012). Yet, density is considered to be a conundrum in the realm of disasters. On one hand, the impact of a natural disaster is higher where people are more concentrated in low quality urban housing, infrastructure and services (Malalgoda et al., 2013). On the other hand, in well planned urban systems, density can facilitate and contribute to attributes of resilience such as diversity, redundancy and resourcefulness. In this dissertation, variables representing the measures of urban forms are population density, land use mix and building type diversity. Population density measures the number of residents within the neighbourhood divided by the area of the neighbourhood. The population density in the affected neighbourhoods of the study area ranges from 6.38 to 5,512.61 persons per sq.km with an average of 1,642 people per sq.km.

This study utilises a descriptive statistic known as the entropy index to describe the evenness of the distribution of built square footage among five land-use categories (residential, commercial, industrial, services, recreational). The entropy index is based on the following equation (Bordoloi et al., 2013):

$$\text{LUM} = - \sum i = \ln pi^* (\ln pi / \ln n)$$

Where n is the number of different land use type classes in the neighbourhood and pi is the proportions of land in type i in the region. The resulting variable LUM is the land use mix entropy index, which varies from 0 (homogeneous land use) to 1 (most mixed, such as diverse city centres) land use. Building type diversity is calculated using Simpson's diversity formula (Simpson, 1949) below:

$$BTD = 1 - \frac{\sum n(n-1)}{N(N-1)}$$

N is the total number of building types. Here, four types of buildings are investigated: separate houses, semi-detached town houses, apartments and other, n shows the number of buildings in a specific building type. BTD also ranges from 0 to 1 representing the least diverse to the most diverse building types within each neighbourhood.

Non-Urban Form: Control Variables

A number of non-urban form variables, which theoretically and empirically are the established contributors of disaster resilience (Carpenter, 2013b) are considered as control variables in this study, including income, tenure and percentage of single parent families. By adding non-urban form factors as control variables, urban form is placed in the context relative to the many variables already known to affect disaster resilience. Previous studies show that long-term home recovery was weaker among the low income, single parent family and renter-occupied households (Carpenter, 2013a; Zhang & Peacock, 2009). Median family income in the affected neighbourhoods of the study area ranges from $794 to $2,797 per week and the mean percentage of home ownership is 60%, with a standard deviation of 16.

8.3.4. Hypothesis 1

This section tests whether a statistically significant relationship exists between the urban form variables and the disaster resilience proxies. For this purpose, a correlation analysis was conducted and the results are presented in Table7.7. Population density shows a moderate positive correlation with the percentage of the reconstructed properties after ten (0.274*) and thirteen months (0.332**) for all types of damage. This suggests that quick reconstruction among all types of damage were associated with denser neighbourhoods within the study area. In fact, reconstruction of the moderately and severely damaged properties shows the highest correlation with density variables (0.45). Land use mix is not statistically significantly correlated with the disaster resilience proxies (β=.193, p=.08). Building type diversity, on the other hand, has insignificant positive correlation with the disaster resilience proxies except for the percentage of minor damaged homes reconstructed within thirteen months and the percentage of severely damaged homes reconstructed within ten months, 0.34 and 0.27, respectively. The hypothesis that the disaster resilience proxies are significantly related to urban form variables is then confirmed for the density variables. Among the non-urban form variables, income and homeownership are positively correlated with all disaster resilience proxies, especially with the severely damaged properties reconstructed after three months (0.446**).

Table 8.7. Correlation coefficients of Urban Form and Non-Urban Form variables

	% Properties reconstructed in 10 months	% Properties reconstructed in 13 months	% Properties reconstructed in 16 months	% Minor damage Reconstructed in 10 months	% Minor damage Reconstructed in 13 months	% Minor damage Reconstructed in 16 months	% Moderate damage Reconstructed in 10 months	% Moderate damage Reconstructed in 13 months	% Moderate damage Reconstructed in 16 months	% Severe damage Reconstructed in 10 months	% Severe damage Reconstructed in 13 months	% Severe damage Reconstructed in 16 months
Independent Variables												
Population density	.27*	.33**	.19	.23	.39**	.23*	.46*	.38*	.17	.43**	.35**	.32**
LUM5	-.15	-.18	-.22	.01	-.01	-.012	-.15	-.09	-.24	.002	-.20	-.14
BTD	.08	.08	-.67	.18	.34**	.07	.10	.12	.08	.27*	.03	.03
Control Variables												
Med family income	.39**	.38**	.27*	.30**	.32**	.14	.29*	.30*	.08	.46**	.22	.29
% Owner occupied	-.22	-.35*	-.30*	-.22	-.35*	-.31*	-.19	-.21	-.04	-.31*	-.17	-.08
House price	.36**	.31**	.16	.29*	.39**	.14	.28*	.26*	.18	.45**	.16	.16
Damage loss	-.28*	-34**	-.61*	-.55*	-.49*	-.66*	-.23	-.36*	-.61*	-.29*	-.55*	-.52*

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

8.3.5. Hypothesis 2

For this hypothesis the aim is to see whether a statistically significant relationship exists between urban form and disaster resilience while controlling for non-urban form variables. In this study, a number of multivariate regression models are developed for each of the disaster resilience proxies to determine how much of the variation in the dependent variable is explained by the independent variables, and to understand the relative and unique contribution of each independent variable towards disaster recovery.

$$\text{Disaster Resilience} = \beta + \beta\ \text{LUM} + + \beta\ \text{Density} + \beta\ \text{MedFamIncom} + \beta\text{\%BuilTypDiv} + \varepsilon$$

The independence of residuals is assessed by the Durbin-Watson test and other assumptions of homoscedasticity, unusual points and normality of residuals are checked and met. In most cases density contributed to disaster recovery, $p<0.05$. Median family income, single parent family and home ownership variables are entered into the stepwise regression analysis along with population density, land use mix and building type diversity. From non-urban form variables, only family income, which in some models is significantly related to the dependent variable, is presented in the table below. Table 8.8 shows the beta values in association with the variables in each of these models.

Table 8.8. Multivariate regression results

	Resilience Variables		Population Density	LUM 5	Building Type Diversity	Median Family Income	Adjusted R^2
Model 1	% minor damage reconstructed	β	.297	-.092	.077	.109	.208
		P value	.049*	.433	.592	.400	
Model 2	% moderate damage reconstructed	β	.393	-.242	-.280	.072	.274
		P value	.008*	.038*	.008*	.570	
Model 3	% severe damage reconstructed	β	.323	-.320	-.081	.213	.249
		P value	.026*	.010*	.561	.105	
Model 4	% reconstructed in 10 months	β	.119	.044	-.017	.362	.138
		P value	.399	.695	.902	.005*	
Model 5	% reconstructed in 13 months	β	.216	-.037	-.109	.357	.154
		P value	.119	.737	.422	.004*	
Model 6	% reconstructed in 16 months	β	.092	-.327	-.201	.398	.224
		P value	.488	.003*	.125	.001*	

*. β is significant at the 0.05 level (2-tailed)

These models show only 14% to 27% of variance in the reconstruction status (adjusted R^2 between 0.14 and 0.27). Considering the complicated and multi-dimensional nature of urban disaster resilience, it was expected that the adjusted R-squared values would be low. In fact, there are many different factors that can explain disaster resilience variations other than population density, land use mix, building type diversity and income level. However, there are statistically significant predictors in these models which, according to Tabachnick and Fidell (Tabachnick & Fidell, 1996), allow us to draw important conclusions about how changes in the independent variables are associated with the changes in the dependant variables. Regardless of the R-squared, the significant coefficients still represent the mean change in the response for one unit of change in the predictor while holding other predictors in the model constant.

Model 1 explains 21% of variation in the percentage of minor damaged reconstructed, and density among the built environment variables shows higher influence (positive) on resilience, as measured by standardized coefficient. A one standard deviation increase in the population density (1,287 persons per km^2) in this case is associated with 29.7% of a standard deviation increase in the percentage of minor damaged reconstructed, which in turn is equivalent to 2.26% increase in the percentage of minor damaged reconstructed. Given the standard deviation of 7.6 for the minor damaged reconstructed, this is a relatively important effect. Model 2 explains 27% variation in the moderately damaged reconstructed properties by density (β=.393, p<.05), land use mix (β=-.242, p<.05) and building type diversity (β= -.280, p<05). In model 3, density (β=.323, p<.05) and LUM (β= -.320, p<.05) statistically significantly predict 25% of variance in the severely damaged properties' reconstruction.

The analysis indicates that not only the income level, but also patterns of urban development in this case, are associated with disaster resilience. The best individual association with disaster resilience is income level ($\beta=.398$, $p<.001$), closely followed by density ($\beta=.393$, $p<.01$).

As a result, the hypothesis that urban form is significantly related to disaster resilience when non-urban form factors are controlled is then confirmed for the minor, moderately and severely damaged reconstructed properties by the significance of density. The coefficient of other variables of urban form are not statistically significant; however, land use mix is consistently negatively associated with the percentage of moderately and severely damage reconstructed and reconstruction status. The findings presented in Table 7.8 suggest that the percentage of severely and moderately damaged properties reconstructed over 16 months has the highest contribution from density ($\beta=.393$, $p<.01$).

8.3.6. Hypothesis 3

It has been hypothesised that the relationship between population density, land use mix and disaster resilience is non-linear. The purpose of this analysis is to identify whether there is a kind of threshold where recovery process shifts as a function of population density or land use mix; and to clarify the linearity or nonlinearity of their relationship. In order to do so, in this section the Jenks natural break classification method (Jenks & Caspall, 1971) is used to convert population density and land use mix into categorical data to help detect changes; and the relationship between resilience variables to be detected at different levels of density and land use mix. The results show that the correlation between resilience and land use mix has not been statistically significant, as shown in Table 2, and further classification analysis found no specific pattern of relationship between land use mix and disaster recovery.

The relationship between population density and the percentage of properties reconstructed within 10, 13 and 16 months are presented in Figure 7.1 from left to right, respectively. The left diagram shows that after 10 months the recovery process in the low and high density areas has a shift while low, medium and high density areas have a positive increasing relationship with recovery. The nature of these nonlinear relationships between density and disaster recovery is more evident in recovery 13 months and 16 months after the disaster. Although it still shows an increasing trend, more fluctuations are detectable at the two ends of the density spectrums for the low and high density areas. The reason for this could be attributed to the low exposure of properties in the low density areas and high exposure and complexity and interdependency in high density and mixed urban areas.

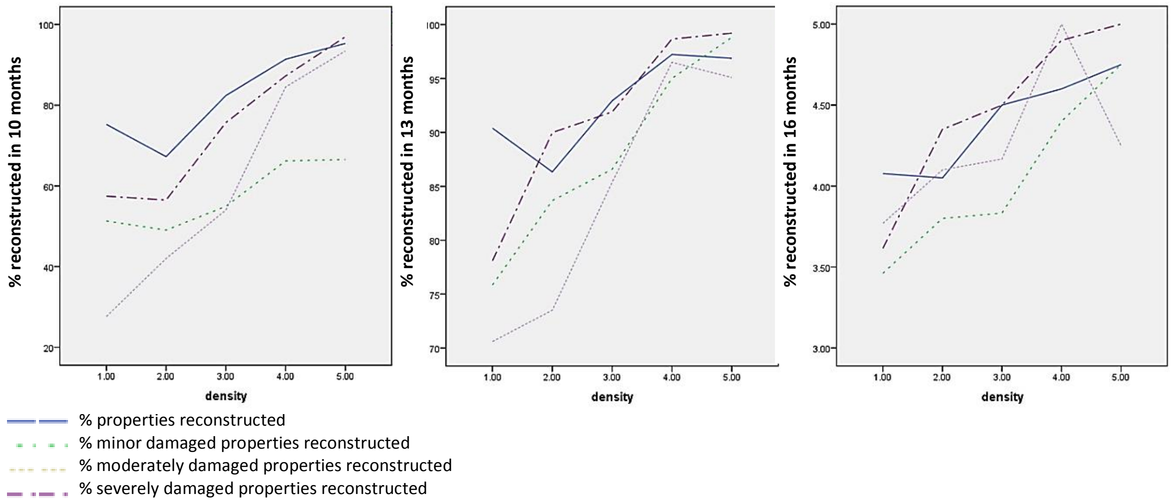


Figure 8.1. Population density and percentage of reconstruction within 10, 13 and 16 months of the flood

In the realm of disaster planning, population density has been viewed negatively as it exposes more people and assets to disasters and creates evacuation problems (Allenby & Fink, 2005; Brody et al., 2011; Carpenter, 2014; Lall & Deichmann, 2011). However, Berke et al. (2009) demonstrated that conventional low density development patterns provide a partial explanation for increasing per capita losses from natural disasters. They suggest there is an emerging demand for new urbanism in countries such as Australia and the United States, which besides the exposure and evacuation problems of dense urban areas, considers other impacts of urban density in the developed countries, namely bringing wealth and coping capacity. In the event of a disaster, density can facilitate the response and recovery process by contributing to resilience attributes such as redundancy, diversity, efficiency, interdependency and resourcefulness. Denser areas in urban settlements usually have better coping capacity in terms of their shelter and medical capacity and their ability to restore systems to their pre-disaster levels (Collier et al., 2013). This study shows that when high density is associated with high incomes, the recovery after a disaster is quicker. For example, in neighbourhoods with low population density and high levels of income (such as Fig Tree Pocket, Tennyson and Anstead in the study area), the reconstruction progress was not as quick as in neighbourhoods with medium density and medium income (such as Balmoral, Bulimba and Paddington).

Although the results in this section extend the association between urban form and disaster resilience, it has several limitations that should be considered. First, disaster resilience is a multi-dimensional concept, so finding a unique proxy as an external indicator that covers all aspects of resilience was not achievable. A second limitation relates to scale. The data is obtained at the neighbourhood level which means investigating the relationship between density and resilience at other scales may yield different results. The final limitation is using a single case study, which suggests the results are not necessarily generalizable for all other urban contexts.

8.4. Summary

In this chapter the validity of the proposed index (NDRI) and its components is examined. The NDRI demonstrates content validity as it includes all possible domains reflected in the intended phenomenon for measurement. The construct validity is investigated by zero-order correlation between the NDRI, its components and sub-components and recovery outcome variables. Moreover, the criterion-related validity is studied by different regression analyses. Data from the DARMsys database provides the convergent real-world evidence for these analyses. The discriminant evidence of the construct validity is examined by differences in correlation between the NDRI and the SoVI and Brisbane/Ipswich dummy and recovery outcomes.

The construct validity is confirmed by demonstrating an expected positive correlation of the NDRI with recovery status of each neighbourhood after the flood, and an expected negative correlation with the level of damage loss in each neighbourhood. These results suggest that neighbourhoods with resilience attributes are more likely to suffer less damage due to a flood and recover quickly after a flood. The risk exposure component within the NDRI demonstrates a relatively low association with recovery progress and a relatively high correlation with damage loss. This can be attributed to the mixed effects of risk exposure. On one hand, it contributes to the damage level and negatively contributes to resilience, and on the other hand it contributes to recovery progress, since the more exposed areas could have improved their capacity to quick response and recovery. The results also suggest that there is a positive correlation between the NDRI and the Brisbane and Ipswich local government dummy variable (0.676**). This finding implies that the neighbourhoods within the Brisbane local government area are more likely to be resilient and more likely to have improved their resilience related capabilities, such as hazard mitigation and disaster preparedness.

The positive correlation between risk exposure and not vulnerable population and human capital suggest that the neighbourhoods located in high flood risk area are more likely to have more human capital and residents who are not vulnerable. Similarly, the positive association between risk and NEcoRI, NSoRI and NPhyRI shows that neighbourhoods in high hazard areas are more likely to be socially, economically and physically resilient. These neighbourhoods are more likely to have access to resources and have stable economic resources. On the other hand, the negative correlation between risk exposure and NEnvRI shows that neighbourhoods in high flood risk areas are not environmentally resilient, as this component of the NDRI has a focus on damage and impact. Finally, as theoretically expected, there is a negative correlation between the NDRI and the SoVI which suggests that neighbourhoods with higher NDRI scores have lower social vulnerability scores.

To explore the relationship between the NDRI and the recovery progress over time in the Brisbane and Ipswich neighbourhoods, a series of regression models are calibrated to evaluate the extent to which the NDRI, its components and subcomponents contribute to recovery outcomes. These models are then extended to control for the other factors that may have impacted the recovery progress, such as the degree of damage and the social vulnerability of the affected neighbourhoods. The results suggest that socio-economic indicators, to a great extent, contribute to predictors of the progress of the recovery. A series of regression analyses revealed that 10 months after the flood, the main predictors of recovery progress are social and economic sub-components, while the progress of recovery after 13 months could mainly be predicted by physical and economic sub-components. Environmental and economic resilience sub-components are the strongest predictors of recovery progress 16 months after the flood. Therefore, other than the economic resilience sub-component, which stays the most important predictor of the recovery progress over the time, the social, physical and environmental resilience sub-components become more important respectively during the period.

From the social component, the percentage of homeowners, volunteers and the level of human capital are the indicators verified as contributing to the recovery progress over time in the Brisbane and Ipswich neighbourhoods. The income level and the percentage of the population not employed in primary industries are among the significant predictors of recovery from an economic perspective. Moreover, in the physical component, non-single family detached houses are found to contribute to the recovery progress, as is critical infrastructure such as the percentage of dwellings with internet connection and the ratio of services land area for populations of 10,000. From the environmental perspective, the percentage of residential land not in a flood risk area is found to be an important contributor to the progress of the recovery.

In the last step for validation, the NDRI shows some evidence of incremental validity. It is confirmed that the NDRI contributes uniquely to the prediction of recovery progress which could not be achieved by the SoVI or damage level. Overall, the results of correlational and regression analyses confirm the construct and criterion-related validation of the NDRI which implies that the measure is theoretically and empirically valid.

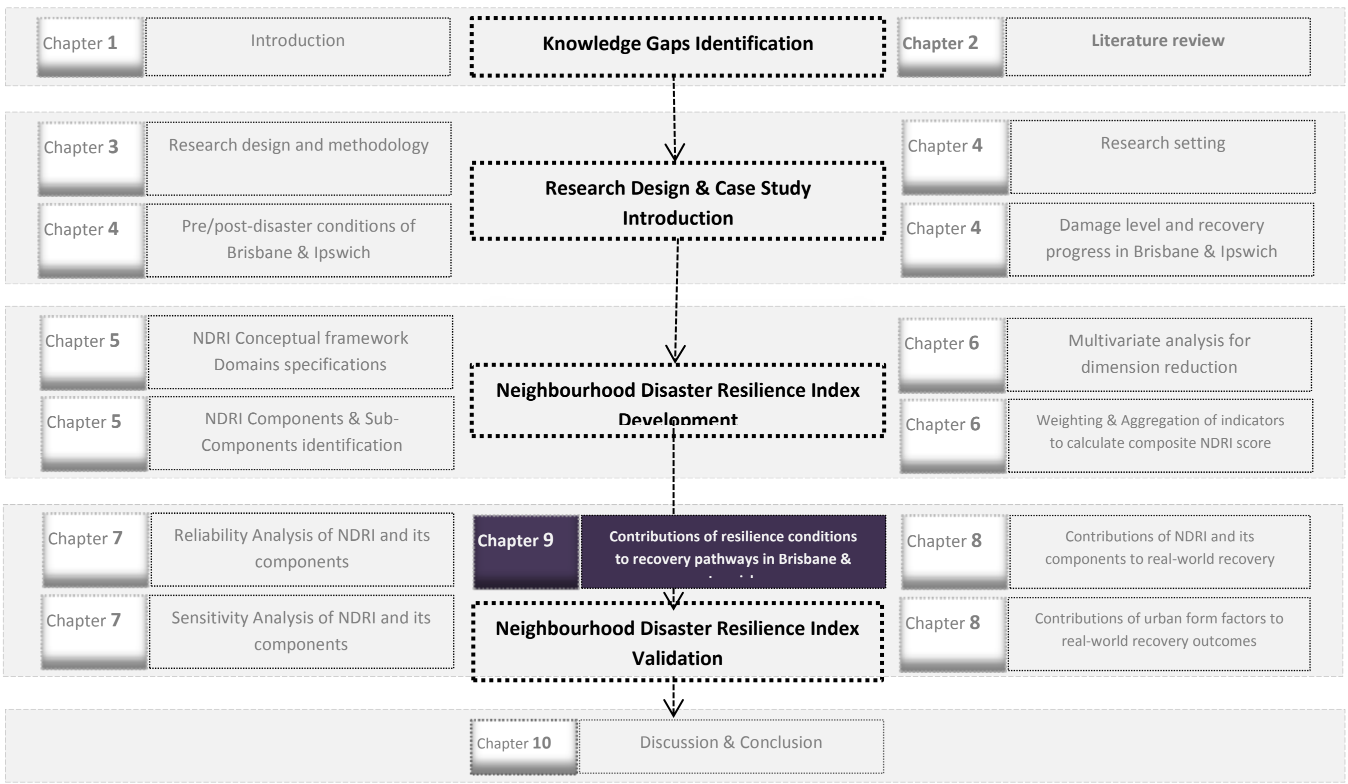
In this chapter the contribution of urban form factors to recovery progress was examined in detail since the relationship between the NDRI, recovery outcomes and urban form show great potential as a physical indicator of resilience. This analysis demonstrates the importance of design and development patterns that can facilitate the recovery and reconstruction process. From the information gathered for the analysis, physical attributes such as density and land use mix explain some degree of the differences in the ability to recover in the Brisbane and Ipswich neighbourhoods. The models displayed good explanatory power (R-squared of 0.38) of the built environment variables, with population density having the most influential (and a positive) effect on resilience, as measured by standardised coefficients. The results show that tight neighbourhoods recovered more quickly than spread out areas. This pattern can be observed after Hurricane Sandy which hit New York in 2012 (Chakrabarti, 2013). Of the non-urban form variables, median family income has the most influential effect on resilience, and this is greater than the effects of any of the built environment variables. The land use mix and building type diversity have a weak effect on recovery. These variables were entered into the model to see whether they improved recovery by contributing to diversity. Despite the limitations of this study, the findings offer a baseline for future studies investigating the link between built environment and disaster resilience. Further research could offer a step forward in disaster planning and policy making to shift from an isolated standalone mitigation and recovery perspective to an integrated development practice.

In a different study we examined the impact of urban form variables on disaster resilience of neighbourhoods after the flood. There are some indications in the literature on the effects of urban form factors, such as discussions on the role of density and land use mix in disaster resilience. Allan et al. (2013), for example, investigated the role of urban morphology on the recovery process after earthquakes, and suggested that integrating resilience attributes into design and development strategies increases the capacity of urban areas in response to, and recovery from, disasters. Very few studies have utilised time series data to examine and contextualize the recovery of neighbourhoods after disasters. Carpenter et al. (2013b) used the return of occupied housing units as a proxy for examining the recovery of neighbourhoods after Hurricane Katrina on the Gulf Coast, USA. They suggest that at suburb level, certain characteristics of the built environment, such as land use diversity and density, influence and support social capital and place attachment, which then facilitate disaster resilience and recovery.

Disaster mitigation and recovery create a ‘density conundrum’ in the context of urban planning. On one hand, compact development can specifically direct land uses, infrastructure systems and socioeconomic activities to non-hazardous areas and also facilitate improved access to resources, services and amenities by bringing in diversity (Chang & Shinozuka, 2004; Lall & Deichmann, 2012). On the other hand, high densities inherently pose a variety of risks: fire, building collapse and violence. It can result in a loss of permeable surface and can also increase the exposure of people and assets, particularly where poor quality and ill-maintained infrastructure and low-quality buildings come into play. However, zoning ordinances can reduce exposure by limiting the development or the density of human occupancy in particularly hazardous areas, by creating or maintaining open spaces, and by limiting the placement of critical facilities such as hospitals, power plants and schools (Godschalk et al., 1998). Thus, the answer to this density conundrum in the context of disaster resilience is argued to be an urban form that allows communities to minimize these contradictory aspects. The findings from the literature suggest that resilient cities need to embrace diversity, density, mix of uses, users, building types and public spaces (Allan & Bryant, 2011b; Jha et al., 2013).

Chapter 9
Index Validation

Contribution of Resilience Indicators to Recovery Outcomes in the Brisbane Neighbourhoods Following the 2011 Flood



9. Index Validation - Contribution of Resilience Indicators to Recovery Pathways

9.1. Overview

The results of the regression analyses in Chapter 8 suggest that the recovery from the flood in the Brisbane and Ipswich neighbourhoods is driven by social and economic factors of disaster resilience. However, between 54 and 87 percent of the variance of the regression models is left unexplained (pseudo R^2 ranged from 0.13 to 0.46 in Table 8.2). This means that extraneous variables not measured to a large extent drive the recovery process. These variables could include local governance decision-making, the provision of recovery funds, as well as the contribution of social capacity that is difficult to quantify. Therefore in this chapter these variables are used to perform a qualitative comparative analysis of neighbourhoods' recovery pathways and seek to answer the following research question.

- What combinations of pre-disaster conditions and post-disaster factors built pathways to recovery?

Methodology

One goal of this research is to comparatively analyse neighbourhood recovery after a flood event. Therefore, given the scarcity of comprehensive comparable quantitative data, a cross-case qualitative comparative analysis (QCA) based on data from surveys and recovery reports to assess the recovery process is used. The first step in QCA involves identifying a particular outcome of interest, besides the conditions that are theorized to have an impact on the outcome.

The pre- and post-disaster conditions of each neighbourhood are evaluated along with damage and recovery outcomes. The housing reconstruction after 10, 13 and 16 months is considered as indicators of recovery outcomes, and damage level as well as with government financial assistance are used as indicators of post-disaster conditions.

Since there are a wide range of data values for conditions and outcomes, the fuzzy set method is used in which each of the conditions and outcomes are assigned a value from 0 (completely out of the set) to 1 (completely in the set). Therefore, the indicators of each condition are aggregated and a minimum-maximum scaling method is used to calibrate the data to a fuzzy-set score.

Housing reconstruction is calculated using the longitudinal field survey damage data provided by the Queensland Reconstruction Authority. The percentage of housing stock reconstructed in each time point for each neighbourhood is calculated and then calibrated using a minimum-maximum scaling method. Four neighbourhoods (Paddington, Greenslopes, Kholo and Sinnamon Park) were fully recovered within 10 months after the flood and were rated as 1. While in Goodna and Yeerongpilly, less than 50% of the affected properties were reconstructed after 10 months and were rated as 0. The same methods are used to calibrate housing recovery after 13 and 16 months.

These data were then imported and analysed using fs/QCA software. The truth table was built within the software, which summarizes the configurations of neighbourhood conditions. To generate an intermediate solution for successful recovery, assumptions were made about the presence or absence of the condition based on the researcher's knowledge. These assumptions are explained below in more detail. Moreover, two important factors are considered in this pathways analysis (Ragin et al., 2008): consistency (which shows the extent to which the neighbourhoods represented by a particular configuration have the same recovery outcome); and coverage (which shows how many of the neighbourhoods are explained by a particular configuration).

9.2. The Methodology of Comparative Recovery Assessment

The fuzzy-set qualitative analysis used in this chapter provides a middle ground between case study and statistical analysis through set theory and fuzzy logic. First, the recovery outcomes are identified along with the pre-disaster and post-disaster conditions that theoretically could affect recovery outcomes. Then, the procedure for variable calibration and preparing a contradiction-free truth table is presented, along with the qualitative analysis to identify the conditions that support housing recovery.

9.2.1. Variable Identification

9.2.1.1. Neighbourhoods Recovery Outcomes

As discussed in Chapter 4, disaster recovery has a dynamic and complicated nature, and monitoring and evaluating recovery progress is a multidimensional concept approached as a social, economic, design, management, finance and planning problem. Many previous studies on disaster recovery have used qualitative and subjective information, obtained by social audits and participatory methods (e.g. focus group meetings, household surveys and key informant interviews). For example, Longstaff et al. (2010) used a qualitative approach and proposed a framework for assessing the resilience of five urban subsystems: economic, environmental, physical, civil society and governance. They (Longstaff et al. (2010)) investigated the adaptive capacity (institutional memory, innovative learning and connectedness) and the robustness of resources (performance, diversity and redundancy) within each subsystem. The World Bank's Global Facility for Disaster Reduction and Recovery (GFDRR), along with the United Nations Development Program (UNDP) and the European

Union (EU), are currently developing a disaster recovery framework (DRF) guide by assessing global good practices. This assessment is mostly qualitative, using in-depth interviews with key government partners (GFDRR, 2015). Qualitative comparative analysis of recovery has also been used by other scholars to compare recovery strategies, capacity and resources in different areas (Allan & Bryant, 2011a; Olshansky et al., 2005).

Recently a series of quantitative, systemic and objective recovery studies have been conducted using direct observation and non-participatory methods (e.g. remote sensing, repeat photography and advanced field survey techniques) that allow detailed observations (Bevington et al., 2011; Finch et al., 2010); (Jordan & Javernick-Will, 2013; Miles & Chang, 2003). These tools have their own strengths and weaknesses and have been used in previous recovery studies to collect different forms of data (subjective-objective, quantitative-qualitative, cross-sectional-longitudinal, primary-secondary, etc.). Quantitative recovery assessment is mostly conducted by recovery indicators. For example, Brown et al. (2010) in the Recovery Project conducted by the Centre for Risk in Built Environment at Cambridge University identified 24 recovery indicators in six major categories of vulnerability, livelihoods, housing (including drinking water access), services, environment (including vegetation and removal of floodwater sand and debris) and infrastructure (including road access and reconstruction). However, the most frequently used recovery indicators are reconstruction of houses, critical facilities and lifelines, noncritical facilities and lifelines, transportation systems, number of building permits and population return (Jordan & Javernick-Will, 2013).

These two distinct quantitative and qualitative approaches are distinguishable in the literature concerning disaster recovery assessment. Quantitative methods typically use a series of indicators (performance indicators) for assessing the recovery as shown in Table 9.1. On the other hand, researchers such as Rubin et al. (1985) point out that it is difficult to unravel and measure disaster recovery through purely quantitative data. Qualitative approaches typically include case study analyses, which can provide valuable insights into the complexities, politics and processes of disaster recovery. However, quantitative assessments using recovery indicators facilitate comparative recovery assessment.

Table 9.1. Recovery indicators extracted from content analysis of the literature

	Category	Indicators/Type	Reference
Quantitative	Social Indicators	Population return Perceived quality of life Social service availability	(Finch et al., 2010)
	Economic Indicators (Livelihood)	Employment GNP/government revenue Household income Number of businesses Standard of living	(Liu et al., 2006)
		Open hotels Open retail food establishments Recovery of livelihoods	
		Labour force size Unemployment rate Population employed in key industries	
	Infrastructure Indicators (Housing, Transport, …)	Critical facilities and lifelines Former customers using electric, water, gas, waste services Open hospitals, childcare centres	(Cheng et al., 2015; Liu et al., 2006; Zhang & Peacock, 2009) (Cheng et al., 2015; Comerio & Blecher, 2010; Comerio, 2006; Liu et al., 2006; McCarthy & Hanson, 2008; Stevenson et al., 2010)
		Noncritical facilities and lifelines Open schools, libraries	
		Transportation & accessibility Operational buses and streetcars and their routes	
		# Homes sold or for sale Fair market rent for a two bedroom unit Appraisal building value--average home sale price Value of new private housing units authorised by building permits #Buildings permits issued Housing reconstruction rate	
	Environmental Indicators	Debris removal Air quality Erosion Water quality Change in land cover and public open space	(Stevenson et al., 2010)
	Institutional (Emergency Response)	# HHDs in trailers and manufactured homes # HHDs receiving housing assistance # Hotel voucher holders Distribution of total federal allocations	(Liu et al., 2006)
Qualitative	Case Study Analysis	Single case	(Olshansky, 2005)
	Qualitative Comparative Analysis	Comparative	(Jordan et al., 2014)
	Resilience Attributes Examination		(Allan & Bryant, 2011b)
	Adaptive Capacity and Robustness of Resources		(Longstaff et al., 2010)

Considering the context and scale of the analysis and data availability, this research defines the applicable recovery outcome with a focus on housing reconstruction. Housing recovery could represent the return of a community's normal daily activities. It is one of the key dimensions of the recovery process which also influences other recovery dimensions (Bolin, 1994; Comerio, 1998). The Damage and Recovery Monitoring dataset (DARMsys) is used to track the reconstruction process in the affected neighbourhoods. The same two recovery outcomes used in Chapter 8 are also used in this chapter. As the reconstruction monitoring audits were conducted every three months after the flood for four rounds, the percentage of recovery is calculated for 10, 13 and 16 months after the flood. These proxies are based on the level of changes in the aggregated damage loss and are described in Chapter 4.

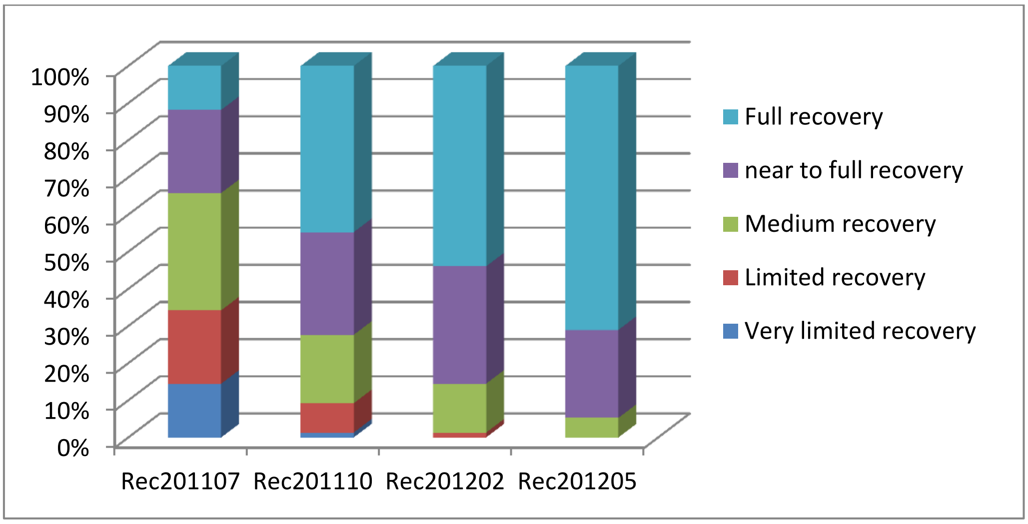


Figure 9.1. Percentage of housing recovery

9.2.1.2. Neighbourhoods Contextual Conditions

Inherent Conditions

The assets or deficiencies in a neighbourhood can be indicators of the disaster impact as well as its recovery (Tierney 2007). Such conditions were discussed in detail in Chapter 5 to identify the resilience/vulnerability indicators at a neighbourhood level. These conditions are hypothesized to influence the resilience (absorbing the impact and quick recovery); and are based on a content analysis of the literature (Jordan & Javernick-Will, 2013). For the qualitative comparative analysis of recovery paths, six pre-disaster conditions that can affect neighbourhood recovery processes are considered based on the regression models in Chapter 8. They include: human capital; economic stability; non-single family detached houses; house price; percentage of residential land in flood risk area; and social vulnerability index (SoVI).

A large body of research has focused on how social vulnerability influences recovery patterns (Bolin, 1994; Cutter et al., 2003; Finch et al., 2010; Fothergill et al., 1999; Tierney & Bruneau, 2007). It is argued that socially vulnerable populations are more likely to live in hazardous locations, less able to access services after a disaster and less likely to have resources for rebuilding. Social vulnerability is typically assessed using the SoVI index. Economic stability for recovery is characterised by three indicators: average income level; percentage employed; and home owners as reported in the 2011 Australian Census. Table 9.2 shows the list of pre and post disaster conditions that may affect the recovery progress of the neighbourhoods.

Table 9.2. List of pre- and post-disaster conditions of neighbourhoods

	Conditions Category	Conditions	Conditions Attributes
Pre-disaster conditions	Socio-Economic	SOVI	Social Vulnerability Index calculated based on Cutter et al.'s (2003) guidelines
		Human capital	Socio-Economic Index for Areas adopted from Australian Bureau of Statistics
		Economic stability	Calculated based on the principle component analysis of economic factors in NEcoRI
	Physical	Urban form	% Not single family detached houses
	Environmental	Hazard exposure	Percentage of residential properties not in flood zone
Post-disaster conditions	Economic	Government financial assistance	Calculated based on ACCS data for federal, state and local assistance recipients
		House price change	Calculated from RP data for house value before/after the flood
	Physical impact	Damage loss	Calculated and calibrated based on DARMsys data definitions

Post-Disaster Conditions

Practice-based reports and academic literature both argue that there have been varying post-disaster conditions among the flood affected neighbourhoods in the study area (Bird et al., 2013a; Lo, 2013; Mason et al., 2012). For this research, damage level, house price change and financial assistance (including insurance claims, federal, state and local financial assistance) are considered as key post disaster conditions affecting recovery. The data for these variables were collected from DARMsys, RP online database and ACCS Wave 4 surveys (details of these datasets are explained in Chapter 4). Twenty-six neighbourhoods are covered in these datasets, which is the number of neighbourhoods considered in the QCA analysis.

As noted in Chapter 4, more than 14,000 properties were flooded in Brisbane and surrounding areas. Physical damage is a primary factor in explaining the level of recovery. Moreover, financial assistance following the flood is also a factor in explaining the recovery progress. According to the Queensland reconstruction framework (enquiry, March 2012), the available resources for reconstruction are comprised of federal resources, state resources, local effort, not-for-profit assistance, corporate assistance and international assistance. In this study, a proxy of recovery funding after the flood is calculated using the data available for the recipients of the federal, state and local recovery funding in the ACCS dataset. The recovery funding variable shows the percentage of affected people who have received at least one form of government recovery funding according to ACCS. The recovery funding data are used as post-disaster conditions in comparative analysis of recovery in affected neighbourhoods.

9.2.2. Comparative Analysis Procedure

In order to find the combination of conditions which lead to successful recovery outcomes, truth table analysis was conducted. The output of the analysis was assessed using two measures: consistency; and the coverage of pathways. These measures are the same as necessity and sufficiency, respectively. Consistency shows the degree to which a configuration is a subset of a recovery outcome, while the coverage shows how important a specific combination of conditions is in accounting for a recovery outcome (Ragin, 2008).

9.2.2.1. Variables Calibration

Once the neighbourhood pre- and post-disaster conditions and recovery outcome variables have been determined, raw data for each neighbourhood (either qualitative or quantitative) are collected according to the set definition to develop the truth table and conduct the analysis. After collecting the raw data, they are calibrated from 0 to 1 to define the set. A 0 score represents a case that is completely outside the set and 1 represents a case that is completely in the set.

One of the truth table calibration methods used is direct calibration by using the minimum-maximum scaling method. This method is used for quantitative variables with sufficient available data and a continuous fuzzy set is used with a cross-over point of 0.5. For example, the percentage of residential properties in the flood zone is calibrated by minimum-maximum scaling from 0 to 1.

The indirect calibration method is used for qualitative data to create groupings of cases. To conduct direct calibration, it is necessary to specify three breakpoint values for full membership, full non-membership and crossover point based on external criteria and theoretical knowledge. For example, damaged buildings reconstructed in each neighbourhood after 10 months are calibrated by setting cut-off values for completely out, completely in, and the crossover point (0.5) between in and out of the set. Table 5.2 provides an example of how indirect calibration can be used to assign scores for damage loss.

Table 9.3. Indirect calibration of post flood housing damage

0.00	No damage	No damage at all
0.25	Minimum damage	Structure is habitable but repairs are required
0.50	Moderate damage	Moderate structural damage, property may not be habitable until repairs completed
0.75	Severely damaged	Severe structural damage, property not habitable until repairs are completed
1.00	Totally damaged	Complete failure of major structure components, structure is not habitable

The data for these conditions for each neighbourhood have been collected from the Australian Census. These data are calibrated in the fs/QCA software based on three values that define membership in the set. For the conditions of recovery with multiple attributes, fuzzy scores are aggregated. If all attributes must be present for the case to be considered part of the set, then the minimum of those attribute scores is considered. If the attributes are substitutable, then the maximum score of the attributes are taken and if all attributes are equally important, then the average of the attributes is considered.

9.2.2.2. Necessity and Sufficiency Analysis

In this section, the number of identified conditions is reduced based on necessity and sufficiency analysis of each condition for recovery outcomes. This analysis determines the necessity and sufficiency of each condition for attaining recovery outcomes. Necessity provides a measure of the degree to which the recovery outcome is a subset of a specific condition. Thus, if one condition is present in all neighbourhoods with positive recovery outcomes, then that condition is considered as a necessary condition. Necessity is calculated as shown below (X= condition and Y= outcome):

$$Neccesity = \frac{\sum(\min(X_i\, Y_i))}{\sum Y_i}$$

Sufficiency on the other hand shows the degree to which the condition is a subset of the recovery outcome. It means that every neighbourhood having this condition always has a positive recovery outcome. The sufficiency is calculated as:

$$Sufficiency = \frac{\sum(\min(X_i\, Y_i))}{\sum X_i}$$

The necessity and sufficiency of conditions related to the housing recovery are assessed using the two formulas above. In this study, the cut off points used as necessary or sufficient is 0.8 for necessity and sufficiency.

Table 9.4 shows information about which conditions are necessary or sufficient to produce a successful recovery outcome. One interesting point of necessity and sufficiency analysis is that economic stability is sufficient, but not necessary for housing recovery. According to the thresholds in Tables 9.4, economic stability is considered a pre-disaster condition for recovery from an economic resilience perspective. SoVI is a pre-disaster condition for recovery from a social resilience perspective and the percentage of single family detached houses is considered a pre-disaster physical condition. On the other hand, the damage level, recovery funds and change in house price after the flood are considered the post-disaster conditions necessary for a successful recovery.

Table 9.4. Necessity and sufficiency of neighbourhood conditions for disaster recovery

	PerRec10		PerRec13		PerRec16		Resilience Index	
Condition	Necessity	Sufficiency	Necessity	Sufficiency	Necessity	Sufficiency	Necessity	Sufficiency
SoVI	0.88	0.76	0.84	0.75	0.83	0.83	0.80	0.83
Human capital-SEIFA	0.78	0.66	0.78	0.66	0.79	0.76	0.79	0.81
Economic stability	0.83	0.79	0.75	0.81	0.71	0.86	0.78	0.87
% Not single family detached houses	0.48	0.84	0.42	0.76	0.45	0.90	0.44	0.92
% Residential land in flood risk area	0.78	0.73	0.79	0.72	0.79	0.81	0.77	0.78
~ Damage level	0.79	0.81	0.83	0.74	0.81	0.82	0.76	0.80
Recovery funds	0.71	0.81	0.70	0.80	0.65	0.84	0.55	0.83
House price change	0.76	0.83	.53	.87	0.50	0.92	0.47	0.91

9.2.2.3. Truth Table Analysis

After data collection and calibration, a truth table is drawn together which contains scores for conditions and outcomes for study area neighbourhoods. At this stage, the quality of the truth table is checked to see whether there is a variety of conditions and outcomes in configurations. Moreover, the contradictory configurations (configurations with the same conditions but different outcomes) and counterintuitive configurations (configurations with all negative conditions and positive outcome) are checked. In the case of the presence of such issues in the truth table, the conditions and the calibration procedures are checked again to see whether there is a missing condition that causes this inconsistency and to make sure that the threshold values are chosen appropriately (Ragin et al., 2008).

Setting recovery outcome values

In order to run the truth table algorithm in fs/QCA a value of 0 or 1 is assigned to the recovery outcome for each neighbourhood. Two metrics can be used to set the recovery outcome values: raw consistency and PRI consistency (Ragin et al., 2006). For this research, the raw consistency is used to assign the values for recovery outcomes as it is more straightforward. The raw consistency for the combination of conditions (configurations) is calculated the same way as necessary for individual conditions. The consistency value for outcome variables is required to be of 0.85 or higher to be assigned 1; and other values are assigned 0.

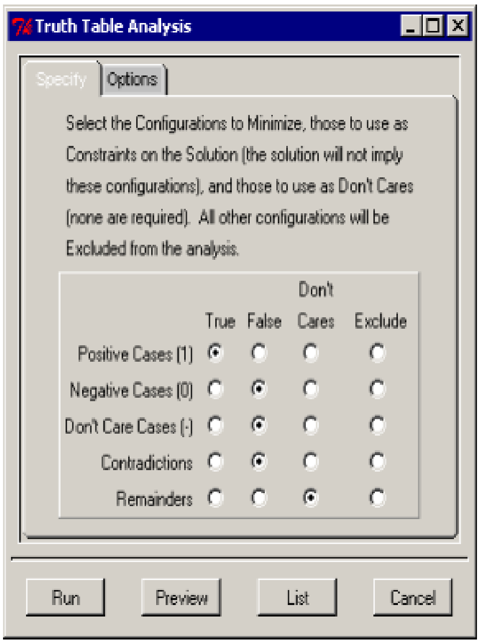


Figure 9.2. Set of assumptions for calculating parsimonious configurations
(Ragin et al., 2008)

Complex, intermediate and parsimonious solutions

In the specification panel for the truth table analysis, to yield the ‘most complex’ solution, positive cases have to be set to True and all other cases to False (Figure 9.2). On the other hand, to get the most parsimonious solution, the positive cases have to be set to ‘True’, Remainders to ‘Don’t care’ and all other cases to ‘False’. In this research, the standard analysis is used as it automatically provides all solutions and it is the only way to derive the intermediate solution. The fs/QCA software conducts counterfactual analysis based on the information about conditions imported manually to develop the intermediate solution.

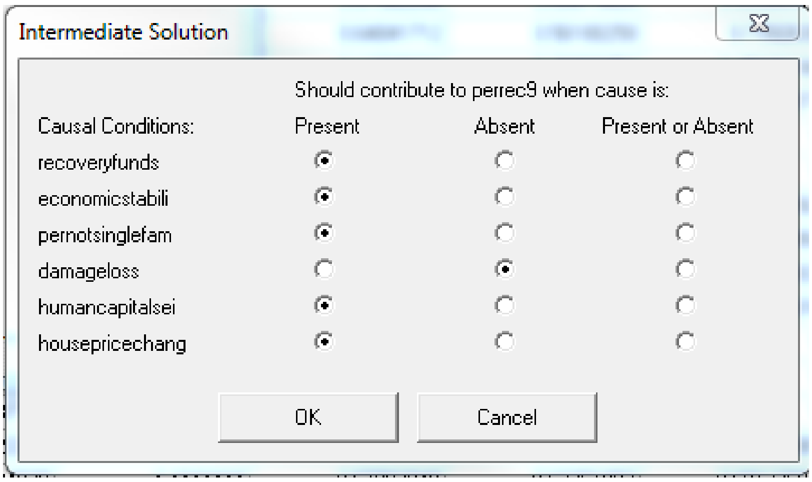


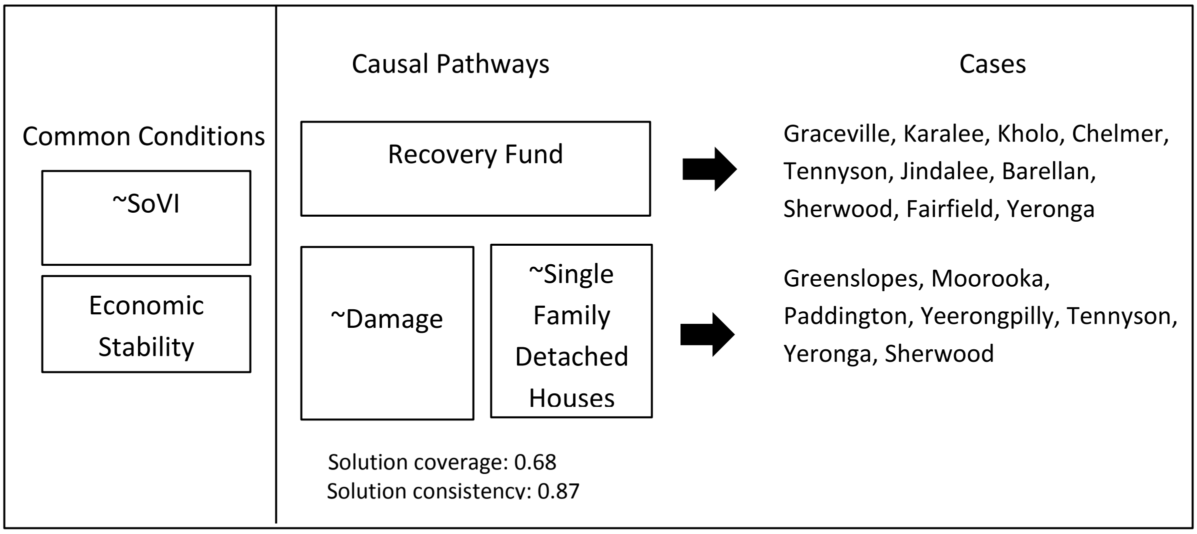
Figure 9.3. Set of assumptions yielding an intermediate solution

9.3. Results and Discussion

Due to the complexity of the study, the analyses are conducted separately for each of the four recovery outcomes. The results associated with each pathway are presented and discussed for each recovery outcome below.

9.3.1. Recovery Outcome 1: Housing reconstruction after 10 months

Housing recovery was assessed based on the DARMsys reconstruction data of flood-affected properties in Brisbane and Ipswich neighbourhoods. Two pathways are identified that are sufficient for successful housing recovery within 10 months after the flood, as shown in Figure 9.3. Two conditions, absence of SoVI and presence of economic stability, are identified with necessity and sufficiency scores above 0.80 which can be considered necessary for housing recovery within 10 months after the flood. About 68 per cent of cases with membership in the successful housing recovery within 10 months also have membership in these conditions. These two conditions appear in both pathways for the first recovery outcome, as shown in Figure 9.3. In addition to those conditions, in order to have a successful recovery outcome, a neighbourhood needs to have either recovery funds *or the low numbers of single family detached houses and be located in the least damaged area*. These pathways are highly consistent, with a score of 0.87, and coverage of 0.68 covering seventeen out of the twenty-six neighbourhoods that achieved housing recovery 10 months after the flood.



Pathways	Raw Coverage	Unique Coverage	Consistency
*~SoVI * Economic Stability*Recovery Fund*	*0.54*	*0.29*	*0.85*
*~SoVI * Economic Stability* ~ Damage Level*% non single family detached house*	*0.38*	*0.13*	*0.92*

Figure 9.3. Pathways to housing recovery within 10 months after the flood

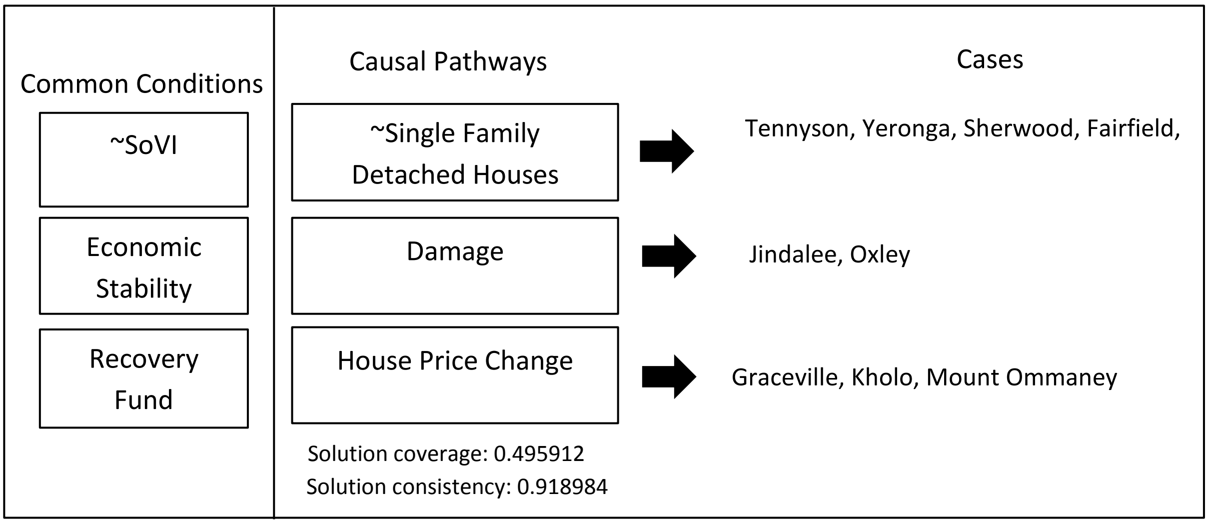
The first pathway shows ten neighbourhoods which recovered within 10 months of the flood including: Graceville, Karalee, Kholo, Chelmer, Tennyson, Jindalee, Barellan, Sherwood, Fairfield and Yeronga. These neighbourhoods with low social vulnerability and high economic stability received recovery funds and managed to reconstruct damaged properties within 10 months after the flood. The second pathway incudes seven neighbourhoods: Paddington, Greenslopes, Moorooka, Yeronga, Yeerongpilly, Tennyson and Sherwood. These are neighbourhoods with high economic stability, low social vulnerability and the low percentage of single family detached houses which suffered relatively less damage loss. Riverview and Redbank had the highest recovery rate within 10 months of the flood, but are missed from the two main pathways. Their recovery can be attributed to the fact that they received high levels of governmental recovery funds, despite having high social vulnerability and low economic stability.

Interestingly, these pathways to recovery within 10 months show that economic stability and absence of social vulnerability are necessary, but not sufficient factors, for successful recovery. Thus, some urban form or post-disaster factors such as recovery funds and damage levels are as important as socio-economic factors.

9.3.2. Recovery Outcome 2: Housing reconstruction after 13 months

Three pathways are identified for housing recovery within 13 months of the flood (Figure 9.4). Three conditions are common between these pathways and can be considered as necessary for housing recovery within this timeframe: economic stability; recovery funds; and absence of SoVI. Almost half of the neighbourhoods with successful housing recovery in this timeframe have membership in the first pathway to recovery within 10 months. In addition to those common conditions, in order to successfully recover within 13 months after the flood, a neighbourhood has to have either a high house price change, damage or low levels of single family detached houses. The consistency of this solution is 0.92 and the coverage is 0.50.

In the first pathway to housing recovery within 13 months of the flood, neighbourhoods such as Fairfield, Sherwood, Tennyson and Yeronga are included, which have fewer single family detached houses in addition to those common conditions of low social vulnerability, high economic stability and access to recovery funds. The second pathway to recovery represents neighbourhoods such as Jindalee and Oxley that suffered less damage and also meet those necessary conditions. The third pathway of recovery represents neighbourhoods with low social vulnerability, high economic stability, had access to government financial assistance and showed potential for house price increase after reconstruction.



Pathways	**Raw Coverage**	**Unique Coverage**	**Consistency**
*~SoVI*Economic Stability*Recovery Fund* Non single family detached houses*	*0.27*	*0.05*	*0.92*
~SoVI **Economic* Stability*RecoveryFund*~Damage	*0.21*	*0.04*	*0.93*
*~SoVI *Economic Stability*Recovery Fund*House Price Change*	*0.39*	*0.11*	*0.92*

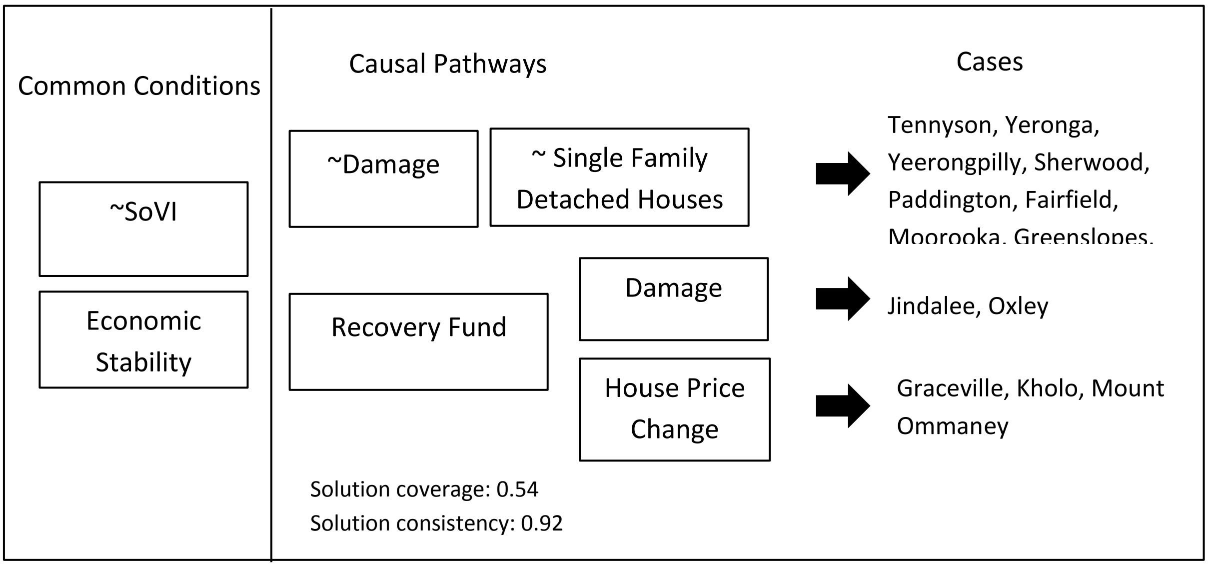
Figure 9.4. Pathways to housing recovery within 13 months of the flood

Other neighbourhoods that recovered and are not represented by these pathways are those with special conditions such as Riverview and Redbank, which received high amounts of recovery funds. In the case of these two neighbourhoods, that condition alone compensated for the lack of other recovery enhancing factors.

Economic stability and the absence of social vulnerability are still necessary conditions for successful recovery within 13 months and the presence of recovery funding is also added to these common conditions in these three pathways. However, urban form, damage or house price change conditions are needed to make a sufficient combination of conditions necessary for successful recovery.

9.3.3. Recovery Outcome 3: Housing reconstruction within 16 months

As was the case with previous recovery outcomes, economic stability and the absence of social vulnerability are common conditions of pathways to recovery within 16 months. All three pathways are identical with previous pathways. The first pathway for housing recovery within 16 months is the same as the second pathway to housing recovery within 10 months and includes the same neighbourhoods. The second and third pathways share the recovery fund condition as well and are identical to the second and third pathways of recovery within 13 months.



Pathways	Raw Coverage	Unique Coverage	Consistency
~SoVI *Economic Stability*Recovery Fund*~Single Family detached houses	*.34*	*.15*	*.94*
~SoVI *Economic Stability*Recovery Fund*~Damage	*.20*	*.03*	*.96*
~SoVI *Economic Stability*Recovery Fund*House Price Change	*.35*	*.10*	*.93*

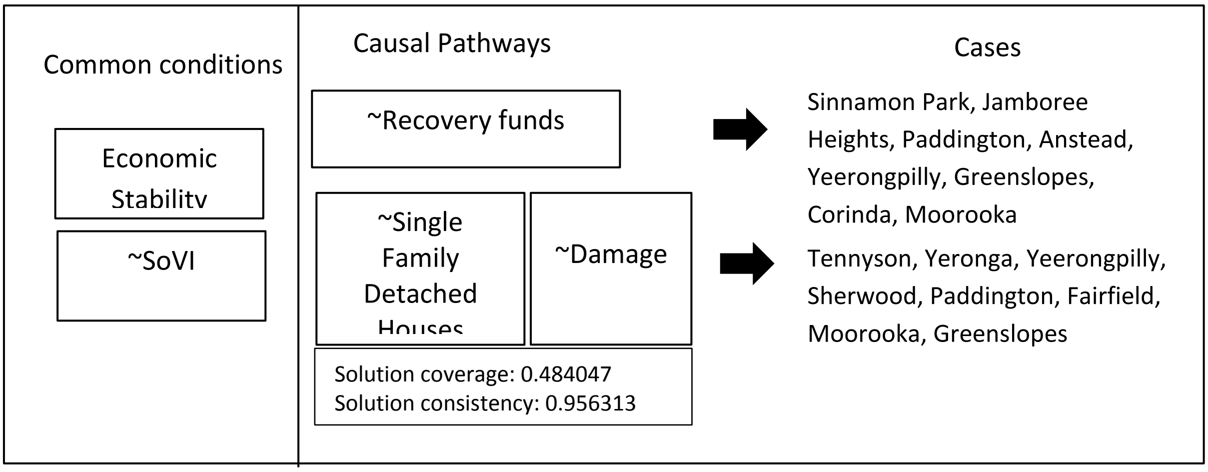
Figure 9.5. Pathways to housing recovery within 16 months after the flood

In addition to common socio-economic conditions, in neighbourhoods with high level of damage, recovery funding and house price changes are important factors in recovery. In neighbourhoods with low damage levels, urban form is critical for recovery, measured as the percentage of non-single family detached houses.

9.3.4. Recovery Outcome 4: Housing resilience index

The two pathways to gain successful recovery identified in this section are the same as the pathways to recovery within 10 months of the flood, though with a lower coverage (0.48) and higher consistency (0.96). Economic stability and absence of social vulnerability appear in all pathways to all recovery outcomes which confirms previous research (Birkmann, 2006; Cutter et al., 2006; Gall, 2007; Timmerman, 1981).

The results for the individual recovery outcomes suggest that many of the same conditions (e.g. social vulnerability and economic stability) are important for different outcomes. It should be noted that the coverage score of 0.69 shows that there are some neighbourhoods which are not represented by these five pathways. For instance, Gailes and Redbank, despite their high social vulnerability and low economic stability, are in the successful recovery set. Both neighbourhoods received high amounts of recovery funds, which are hypothesized to lead to successful recovery. It is also possible that recovery of the neighbourhoods which do not appear in the identified pathways could be explained by other variables which are not included in these analyses due to lack of data, such as the data related to the percentage of successful insurance claims.



Pathways	**Raw Coverage**	**Unique Coverage**	**Consistency**
Economic Stability ~SoVI * ~Recovery Funds*	*.39*	*.16*	*.98*
Economic Stability ~SoVI *~Damage*~Single Family Detached Houses*	*.32*	*.98*	*.95*

Figure 9.6. Pathways to achieve high RecIndex value

9.4. Summary and Conclusion

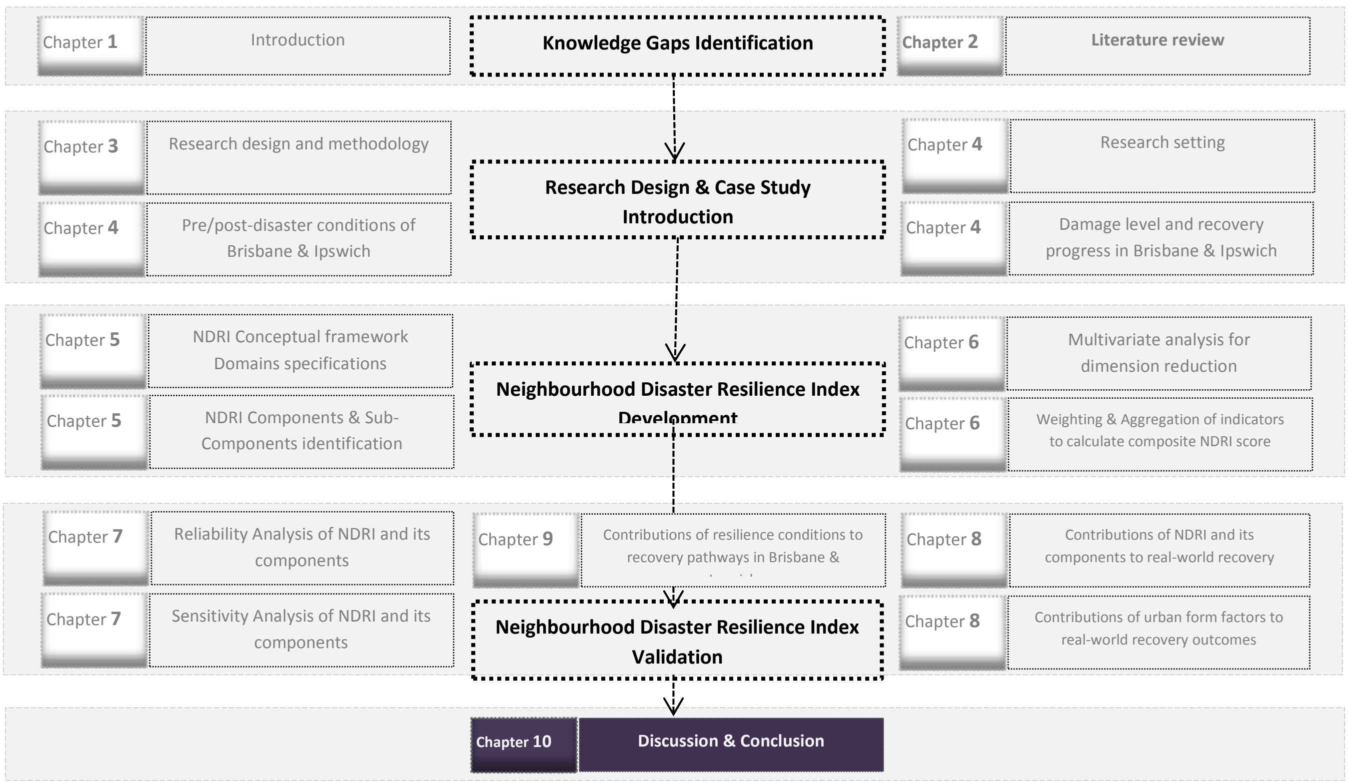
This research examined the link between five resilience attributes and housing recovery outcomes in 26 flood-affected Brisbane neighbourhoods. Fuzzy set qualitative comparative analysis was used to analyze the conditions and recovery outcomes in each neighborhood. The resilience attributes and recovery outcomes assessed in earlier chapters are used in this analysis. The recovery outcome variables used in this analysis are the percentage of properties reconstructed within 10, 13 and 16 months after the flood. The pre-disaster conditions used in these models are economic stability, SoVI and percentage of non-single family detached houses. The post-disaster conditions considered included damage loss, house price change (%) and recovery funds. The necessity and sufficiency of each condition for recovery was evaluated and five different pathways for recovery are identified.

The results show that there were several pathways combining pre-disaster situations and post disaster conditions which led to recovery, as measured by the housing reconstruction after the flood. For instance, post-disaster financial assistance played a critical role in the recovery of neighbourhoods like Riverview and Graceville; on the other hand, a combination of relatively low economic stability and social vulnerability also led to successful housing recovery. The results identify the pre-disaster and post-disaster causal and mediating factors associated with housing recovery in 26 Brisbane and Ipswich neighbourhoods after the 2011 flood.

The results are consistent with the earlier studies that linked economic stability to recovery (Jordan & Javernick-Will, 2013). However in this research, economic stability is not necessary for recovery (as demonstrated by Table 9.4), but it is sufficient (as shown in Table 9.4), meaning that communities with sufficient funds are likely to recover regardless of other conditions. This makes sense because community members with financial resources are able to survive even without jobs and to rebuild without waiting for external aid. However, the pathways show that even a low-income, uninsured neighbourhood, such as Riverview, can recover due to the presence of high levels of human capital, recovery funds and changes in house prices. Therefore, despite the appearance of economic stability and human capital in all five identified pathways, none of them are necessary across all neighbourhoods. This insight is enlightening where community resilience needs to be improved through different pathways. While economic stability and human capital might be difficult to modify resilience, planners can provide additional support to areas of concentrated social vulnerability during the recovery process.

The combination of conditions identified in the analysis reveals that there are different areas that communities can invest in to build a more resilient community that can successfully recover from future floods. Communities could have different recovery pathways. For instance, disaster resilience can be improved by reducing social vulnerability and increasing economic stability. Strengthening human capital and social networks in communities with high levels of social vulnerability can contribute to the resilience of neighbourhoods. When these conditions are not present, resilience can be improved through access to resources and better land use management. The results also show the importance of urban form. Neighbourhoods with more compact designs and less single family houses recover more quickly. This suggests a density conundrum between density, exposure and recovery. Thus in cities like Brisbane (and many other cities around the world), which have been built on a floodplain where flooding cannot be completely avoided, attention to the density, building type and development patterns could improve resilience.

Chapter 10
Discussion and conclusion



10. Summary and Conclusions

10.1. Overview

The overall aim of this research was to improve the operationalisation of the concept of disaster resilience in urban contexts and to understand the relationships between resilience indicators and real world resilience outcomes. This goal is addressed by developing a neighbourhood disaster resilience index (NDRI) which is checked for its theoretical soundness and empirical validity. In this chapter the different steps carried out to develop this measure (NDRI) and the summary of findings are discussed. The chapter concludes by summarizing the theoretical and practical contributions of the thesis. Lastly, the limitations of this research and some ideas suggested for future research are presented.

10.2. Summary of Findings

As discussed earlier in Chapter 1, there are a few gaps in the current literature on operationalizing disaster resilience. Measuring disaster resilience at a neighbourhood level in the Australian context has not been addressed comprehensively considering its physical, social, and economic and environment conditions. Moreover, the reliability and validity of existing models which have measured disaster resilience has not been addressed. Therefore, two research questions in this research bridge the gap by following a series of analytical steps required for robust index development and validation. The sections below present the findings of each chapter related to each research question.

RQ1. How can an urban disaster resilience model be developed at neighbourhood level?

To answer this question, a set of sub-questions were developed to guide the procedure needed to develop the intended index.

RQ1.1. What is the nature of the resilience construct's conceptual domains and properties?

The first sub-question is addressed in Chapter 5 by content analysis of urban resilience literature and examining previous models on resilience, vulnerability and adaptation capacity. A theoretical framework for the development of the intended index is proposed and more specifications of the intended model were identified. The focal construct in this research is considered as a function of the resilience attributes within each resilience component. The focal construct/model in this thesis is considered as an exogenous second order construct with multiple first order sub-dimensions as formative indicators.

RQ1.2. What are the key indicators of disaster resilience at neighbourhood level?

To address this question, the indicators of resilience were identified in Chapter 5 by cross-classification of resilience components and resilience attributes. Out of the 93 variables on the wish list, 76 were deemed appropriate to measure the resilience at neighbourhood level based on two criteria. First, it was essential that variables were justified, based on the literature on the variable's relevance to resilience. The second criterion was that variables must be meaningful at the scale of this study, neighbourhoods.

RQ1.3. What set of variables provides a parsimonious indicator set of disaster resilience at the neighbourhood level?

The underlying structure of the data was examined by a correlation matrix for each dimension in Chapter 6. This analysis showed that some variables could not be grouped with other variables in the same way that they were hypothesized in Chapter 5. Therefore, the correlation analysis was applied to reduce the redundant variables from 76 to 65. Furthermore, principle component analysis (PCA) was employed to redefine the data using the best linear combination of the items and reducing the number of the variables to a smaller set of 'artificial' variables that account for most of the variance in the original variables. Moreover, principle component analysis played a confirmatory role in identifying the sub-components of each component. Multi-dimensional scaling (MDS) was used to detect the similarities and dissimilarities between indicators, and assess the internal consistency of the data set based on the distances between variables in Euclidean space. As a result of PCA and MDS analyses, 12 variables were excluded from further analysis. The final remaining 53 variables provide the best parsimonious set of indicators for measuring resilience at the neighbourhood level.

RQ1.4. How can the identified indicators be merged into an overall resilience composite index?

Each subcomponent of resilience is treated separately for variable selection and for the analytical processes outlined in this research. In this model, the effect of each sub-dimension on the focal resilience construct was assumed, independent of the effects of the other sub-dimensions. This implied that a change in each individual sub-dimension was sufficient (but not necessary) to produce a change in the meaning of the focal resilience construct. The magnitude of the effect of each sub-dimension was unrelated to the other sub-dimensions and the sub-dimensions were substitutable in the sense that one might compensate for another. As a construct with multiple second order formative sub-dimensions, it was necessary to determine how to combine the sub-dimensions to form the intended focal resilience construct.

Considering the above assumptions, different methods of weighting and aggregation were investigated in Chapter 5 to find the best way of merging the identified indicators into an overall resilience index. Among the parametric and non-parametric methods of weighting methods in the literature, principle component analysis and equal weighting were employed in this study. The overall score calculated with each of these methods are highly correlated (r=0.91**).

Different methods were utilised for aggregation at different levels of the index. The subcomponent scores have been calculated by averaging the individual indicators values to remove the effect of different number of variables in each subcomponent. The overall NDRI score and the scores of each dimension have been calculated using linear and geometric aggregation methods. The sensitivity of using each of these weighting and aggregation methods on the final neighbourhood resilience scores are tested in detail in Chapter 7.

RQ2. How can the neighbourhood disaster resilience model be validated by assessing its contributions to the recovery outcomes?

RQ2.1. To what extent is the proposed model internally sound and robust?

In Chapter 7, the reliability of the proposed NDRI was examined using inter-item correlation analysis for individual reliability assessment and stratified Cronbach alpha coefficients for composite reliability assessment. Considering the multidimensional and formative nature of the NDRI, it did not assume high internal consistency between components. The results on the inter-item correlations showed that the majority of the indicators within unidimensional sub-components of the model are statistically significant and positively correlated ($p < 0.05$, $p < 0.01$), implying a high degree of consistency of these measures. Some variations existed in terms of magnitude and strength of correlations, but overall the correlation patterns were reasonable. In sum, the NDRI which is the composite scale of resilience exhibited an acceptable level of stratified Cronbach's alpha coefficients (0.580), suggesting that it is a fairly reliable measure. On the other hand, the negatively and insignificantly related indicators were dropped from the construct to improve parsimony. This resulted in a refined set of indicators which were used to calculate the second alternatives for each component.

Furthermore, a series of sensitivity analysis was conducted in Chapter 7 to assess the robustness of the index, which revealed a relatively balanced representation of the indicators, and moderate methodological uncertainties. The exclusion of indicators suggested based on the previous section's analysis improved the robustness of the sub-indices in their second alternative.

RQ2.2. To what extent is each indicator, sub-component and component of the NDRI contributing to recovery outcomes?

The validity of the proposed index (NDRI) and its components was examined in Chapter 8. The NDRI demonstrates content validity as it includes all possible domains reflected in the intended phenomenon to measure. The construct validity is investigated by zero-order correlation between NDRI, its components and sub-components and the recovery outcome variables. Moreover, the criterion-related validity is studied by different regression analyses. Data from the DARMsys database provided the convergent real-world evidence for these analyses. The discriminant evidence of the construct validity was examined by differences in correlation between NDRI and SoVI and the Brisbane/Ipswich dummy variable and recovery outcomes.

The construct validity is confirmed by demonstrating an expected positive correlation of the NDRI with the recovery status of each neighbourhood after the flood, and an expected negative correlation with the level of damage loss in each neighbourhood. These results suggest that neighbourhoods with resilience attributes are more likely to suffer less damage due to a flood and recover quickly after the flood. The risk exposure component within the NDRI demonstrates a relatively low association with recovery progress and a relatively high correlation with damage loss. This can be attributed to the mixed effects of risk exposure to disaster resilience. Exposure could contributes positively to the damage level while it is also associated with recovery progress since the more exposed areas could have improved their capacity to quick response and recovery. The results also suggested that there is a positive correlation between the NDRI and the Brisbane and Ipswich local government dummy variable (0.676**). This finding implies that the neighbourhoods within the Brisbane local government area are more likely to be resilient and more likely to have improved their resilience related capabilities, such as hazard mitigation and disaster preparedness.

The positive correlation between risk exposure and not vulnerable population and human capital suggest that the neighbourhoods located in high flood risk areas are more likely to have more human capital and a less vulnerable population residing within them. In the same way, the positive association between risk and NEcoRI, NSoRI and NPhyRI shows that neighbourhoods in high hazard areas are more likely to be socially, economically and physically resilient. These neighbourhoods are more likely to have access to resources and have stable economic resources. On the other hand, the negative correlation between risk exposure and NEnvRI shows that neighbourhoods in high flood risk areas are not environmentally resilient, as this component of the NDRI has a focus on damage and impact. Finally, as theoretically expected, there is a negative correlation between the NDRI and

SoVI which suggests that neighbourhoods with higher NDRI scores have lower social vulnerability scores.

To explore the relationship between the NDRI and the recovery progress over time in the Brisbane and Ipswich neighbourhoods, a series of regression models were calibrated to evaluate the extent to which the NDRI, its components and subcomponents contribute to recovery outcomes. These models are then extended to control for the other factors that may have impacted the progress of the recovery such as the degree of damage and the social vulnerability of the affected neighbourhoods.

The results suggest that socio-economic indicators contribute to recovery progress predictions. A series of regression analyses revealed that 10 months after the flood, the main predictors of the progress of recovery are social and economic sub-components, while recovery progress after 13 months could best be predicted by physical and economic sub-components. Environmental and economic resilience sub-components are the strongest predictors of recovery progress 16 months after the flood. Therefore, other than the economic resilience sub-component which stays the most important predictor of the recovery progress over time, the social, physical and environmental resilience sub-components become more important respectively, during the time.

From the social component, the percentage of homeowners, volunteers and the level of human capital are the indicators verified as contributing to the recovery progress over time in the Brisbane and Ipswich neighbourhoods. The income level and the percentage of population not employed in primary industries are among the significant predictors of recovery from an economic perspective. Moreover, from the physical component, non-single family detached houses are found to contribute to the recovery progress, as is critical infrastructure such as the percentage of dwellings with internet connection and the ratio of services land area per 10,000 head of population. From the environmental perspective, the percentage of residential land not in flood risk areas is found to be an important contributor to recovery progress.

In the last step for validation, NDRI showed some evidence of incremental validity. It was confirmed that NDRI contributes uniquely to the prediction of recovery progress which could not be achieved by SoVI or the damage level. Overall, the results of correlational and regression analyses confirmed the construct and criterion-related validation of the NDRI, which implies that the measure is theoretically and empirically valid.

RQ2.3. To what extent are the urban form variables contributing to recovery outcomes?

The contribution of urban form factors to recovery progress is examined in the last part of Chapter 8 since the relationship between NDRI, recovery outcomes and urban form showed great potential as a physical indicator of resilience. This analysis demonstrates the importance of design and development patterns that can facilitate the recovery and reconstruction process. From the information gathered for the analysis, physical attributes such as density and land use mix explain some degree of the differences in ability to recover in the Brisbane and Ipswich neighbourhoods. The models displayed good explanatory power (R^2 of 0.38) of built environment variables with population density having the most influential (and a positive) effect on resilience, as measured by standardised coefficients. Of the non-urban form variables, median family income has the most influential effect on resilience, greater than the effects of any of the built environment variables. The land use mix and building type diversity have a weak effect on recovery. These variables were entered into the model to see if they improve the recovery by contributing to the diversity. Despite the limitations of this study, the findings offer a baseline for future studies investigating the link between built environment and disaster resilience.

RQ2.4. Which pre-disaster conditions and post-disaster factors and what combinations of them built pathways to recovery?

In Chapter 9, the link between the six most effective resilience attributes identified in Chapter 8 and the housing recovery level over time is examined within 26 flood-affected neighborhoods in Brisbane. Fuzzy set qualitative comparative analysis is utilized to analyze the conditions and recovery outcomes in each neighborhood. The recovery outcomes used in this analysis are the percentage of properties reconstructed within 10, 13 and 16 months after the flood. The pre-disaster conditions used in this model are economic stability, social vulnerability, percentage of non-single family detached houses, and house price change. On the other hand, post disaster conditions considered in the model are damage loss and the availability of recovery funds. The necessity and sufficiency of each condition for housing recovery have been evaluated and five different pathways for housing recovery are identified.

The results showed that there were several pathways combining the pre-disaster situation and post disaster conditions which led to recovery in Brisbane neighbourhoods, as measured by the housing reconstruction after the flood. For instance, post-disaster financial assistance played a critical role in recovery of neighbourhoods like Riverview and Graceville; on the other hand, a combination of low economic stability and low social vulnerability also led to successful housing recovery in neighbourhoods such as Greenslopes. The results identify the pre-disaster and post-disaster causal and mediating factors associated with housing recovery in flood affected neighbourhoods.

The combination of conditions identified in the analysis reveals that there are different areas that communities can invest in to build a more resilient neighborhood that successfully recovers from future floods. Different communities could have different pathways of recovery. For instance, disaster resilience can be improved by reducing social vulnerability and increasing economic stability. When these conditions are not available, resilience could be improved through interventions in issues such as access to resources, land use management, etc. The results also show the importance of urban form in this context. Neighbourhoods with a more compact design and fewer single family detached houses recovered relatively more quickly. Although it may create a density conundrum between high exposure and the capability of recovering quickly, it emphasizes the fact that in cities such as Brisbane which have been built on a floodplain, and where a flood cannot be completely avoided, attention to the building types and development patterns could improve resilience.

10.3. Conclusions

Based on the evidence accumulated from the data analyzed for this study, it can be concluded that the overall goal of this research was achieved. The findings provided conclusive empirical evidence that the neighbourhood disaster resilience index (NDRI) can be used to measure disaster resilience at neighbourhood level. Overall, the findings of this research are promising and provided a valuable contribution to theory and practice as described in the sections below. Moreover, the limitations to this study and some recommendations for future works are presented.

10.3.1. Contribution to Theory

The thesis has made four contributions to disaster resilience and recovery theory. Each is described below.

1. This research provides a validated and verified measurement tool that improves comparative assessments of disaster resilience at the neighbourhood level. The resilience components and indicators were identified from different perspectives and the identified indicators were refined and purified through multivariate analysis and dimension reduction techniques. One of the drawbacks of previous models was their reliance on national data sources that could be inadequate to characterize the local circumstances. However, in this study, local data is also utilized to represent the physical agents and resilient attributes of the case study area. In addition, these indicators are

validated using a real-world recovery data from flood affected neighbourhoods in Brisbane and Ipswich. According to the literature review in Chapter 2, most of the resilience measurement indices are at large scales (national and sub-national level) without comprehensive validation. In most cases, only reliability and internal validity of the indexes is tested, while in this thesis the NDRI is tested for sensitivity, internal and external validity. Moreover, from a methodological point of view, the structure of this thesis offers step by step guidelines for the development of constructs and indexes in different urban contexts, from making theoretically sound framework, to dimension reduction techniques, sensitivity and reliability analysis and validity assessment.

2. The research is innovative in exploring the impact of urban form indicators on disaster resilience and recovery progress using the recovery data of flood-affected neighbourhoods in Brisbane and Ipswich. It is important to not only understand which indicators better represent the recovery process and potentially the resilience of communities, but also its definition of how various factors of resilience interact to influence recovery. Providing sound measurements of what makes some communities more resilient than others permits comparisons across space and time and should provide guidance on structural, economic, social and sustainable policy changes needed for resilience enhancement. Understanding the contribution of the factors that enhance or inhibit resilience provides a step in defining actions to reduce risk, to accelerate recovery following disasters, and to facilitate the acceptance of changes following a significant hazard event. Empirical evidence found a relationship between density and the rate of recovery after the 2011 flood in the Brisbane and Ipswich neighbourhoods.

3. This research extends previous studies by examining the causal links between vulnerability, resilience and multiple recovery outcomes and validates earlier hypotheses that pre-disaster community conditions affect recovery. Building a theory of recovery necessitates examining such links, because while the influence of individual factors on recovery has been well-studied, we still lack an understanding of how such factors interact. This research showed that there are multiple possible pathways to successful recovery. This study is unique in that it compares recovery outcomes of different communities affected by the same disaster. This research builds recovery theory within the context of a specific disaster by determining combinations of conditions that led to recovery. Chapter 4 also expanded on this earlier research by incorporating the effect of post-disaster processes on recovery outcomes. While prior research proposed that recovery processes can be categorized as either independent or dependent (Bates and Peacock, 1989), this research found that both inherent pre-disaster conditions and post-disaster responses by outside organizations were important for achieving recovery. There are a large number of variables that are expected to

influence disaster recovery, and it is important to consider the interactions among them. This dissertation presented a cross-case comparison that analyzed what combinations of factors lead to successful recovery.

4. The weighting and aggregation procedure is a critical step in developing composite indices to achieve a meaningful and balanced combination of the components and sub-components. This has been missing in previous models. In this study it has been addressed by developing different alternatives using different weighting and aggregation methods based on theoretical specifications of the model. Then sensitivity analysis was used to examine the robustness of the decisions made during the development of the composite index, including variables inclusion, weighting and aggregation methods.

10.3.2. Contribution to Practice

The thesis also makes the following contributions to practice.

1. The findings in this thesis can be useful for practitioners attempting to build disaster resilient cities. As a step in operationalizing disaster resilience, developing the neighbourhood disaster resilience index provides opportunities to transition from a descriptive concept to a normative agenda for policy makers and planners at the neighbourhood scale. The NDRI provides a tool for comparative assessment of resilience across neighbourhoods, which could facilitate the adaptive management and policy making through monitoring and evaluation of the NDRI. Moreover, NDRI can help in identifying actions required for risk reduction and guide the policy changes needed for resilience enhancement in different urban sectors.

2. Chapter 9 highlighted the need to look beyond the quantitative rationalization of a resilience index and use it as a basis to generate robust context-appropriate resilience-making activities. The combinations of the pre/post disaster conditions leading to successful recovery were examined. Based on these combinations, planners can build a picture of the resilience of the development proposals and facilitate evidence-based policy and decision making for intervention.

3. The implications of Chapter 8's findings are that improving risk-sensitive land use management and compact urban design could increase the response capacity of neighbourhoods. This could help achieve wider societal goals that support resilient developments. Moreover, it could help policy and decision makers develop new ways of allocating land use, development functions and building types in urban contexts. Local resilience interventions are not only critical for developing adaption strategies to cope with uncertainties, but also for improving practical strategy-making that can enrich the city's economic position. For example, a socio-economically diverse city (diversity as a

resilience attribute) can provide social services that make it an economically attractive place to live and work in spite of disturbances.

4. The resilience attributes within the urban context of the NDRI's framework can assist designers and planners incorporate these attributes into their daily practice for each development project. For example, incorporating redundancy and multi-functionality attributes can assist in applying diversity of the adaptation strategies to urban bio-physical systems, such as low impact development practices such as permeable pavements and urban tree canopies to capture rainfall before it reaches the ground. These features facilitate and diversify the urban stormwater system, decreasing the storm drainage facilities that are needed, and improving the resilience capacity of the system.

5. Finally, the NDRI, can help facilitate communications between researchers, policy makers and the public regarding resilience strategies, thus promoting accountability. Readily available and accessible information is a primary condition for effective public participation. The NDRI can serve as an analytical, communication and collaboration tool that can support decision making, planning and policy development by raising awareness. It can also improve the understanding of the complex, multidimensional concept of resilience, promote discussion and facilitate scenario analysis to examine possible futures.

10.3.3. Recommendations for Future Research

The exploratory part of the thesis (NDRI development) that has examined the characteristics of the neighbourhoods contributing to resilience outcomes has the potential to be adapted to the context of climate uncertainties. However, the confirmatory part (NDRI validation) is limited to riverine flood in the context of the Brisbane and Ipswich neighbourhoods. This gives rise to the need to discuss issues of generalizability, which are partly addressed in Chapter 3. Further improvements can be gained through replicating the NDRI validation in other disaster-affected neighbourhoods. This will give the opportunity to assess whether the propositions presented in this dissertation apply in other contexts and may help to draw more generalized results. Future study could also focus in more depth on some of the conditions that were identified in this research to be important for resilience and recovery. For example, the link between urban form variables and development patterns can be investigated more in detail to offer a step forward in resilience literature and improve understanding of what strategies are effective in disaster planning and policy making to shift from an isolated standalone mitigation and recovery perspective to an integrated development practice.

In addition to potentials in extending this research to address the limitations outlined in previous section, for further improvement of the NDRI, it has the potential to be incorporated in a Decision

Support System (DSS). This integrated model could be expanded to a geo-referenced Shared Learning Platform (SLP) as a resilience decision support system to build a network of stakeholders, practitioners and academics in order to provide a collaborative platform for future mapping and gathering best practices in each sub-component of NDRI. This could facilitate the distributed decision making in networked multi-agent systems within communities and has the potential to contribute to making resilient cities through adaptive management, cyberinfrastructure, social learning and online community development.

Moreover, the NDRI can be expanded using emergent data-driven modelling techniques such as neural networks, game theory and systems theory to address some of the limitations in development of NDRI. For example, utilising systems of systems approach in modelling resilience can help to expand the NDRI to measure resilience as a process rather than a snapshot in time. As Tyler (2014) comments, resilience is evident through the interaction of the system over time as an emergent property of complex systems and cannot be fully represented by snapshot indicators. Utilising systems theory in operationalising resilience in a practical context facilitates capturing the dynamic characteristics of resilience and also to take into account all the possible interactions between the components. Therefore, further expansions of the NDRI could come from utilising and detailing the systems theory approach and describing the relative importance of the various selected indicators and their interaction in a greater development picture for a given situation.

References

Adger, W. N. (2000). Social and ecological resilience: are they related? *Progress in Human Geography, 24*(3), 347-364.

Adger, W. N., Hughes, T. P., Folke, C., Carpenter, S. R., & Rockstrom, J. (2005). Social ecological resilience to coastal disasters. *science, 309*, 1036-1039.

Ahern, J. (2011). From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landscape and Urban Planning, 100*(4), 341-343.

Ahern, N. R., Kiehl, E. M., Lou Sole, M., & Byers, J. (2006). A review of instruments measuring resilience. *Issues in comprehensive pediatric nursing, 29*(2), 103-125.

Alam, K., Herson, M., & O'Donnell, I. (2008). Flood disasters: Learning from previous relief and recovery operations. *ALNAP Lessons Paper. ALNAP and Provention Consortium. http://www. alnap. org/pool/files/ALNAP-ProVention_flood_lessons. pdf*.

Alessa, L., Kliskey, A., & Altaweel, M. (2009). Toward a typology for social-ecological systems. *Sustainability: Science, Practice, and Policy, 5*(1).

Aldrich, D. P. (2012). Building resilience: Social capital in post-disaster recovery. *University of Chicago Press.*

Alizadeh, T. (2015). A policy analysis of digital strategies: Brisbane vs. Vancouver. *International Journal of Knowledge-Based Development, 6*(2), 85-103.

Allan, P., & Bryant, M. (2011a). *The attributes of resilience : a tool in the evaluation and design of earthquake-prone cities*. Paper presented at the International Conference on Building Resilience: Interdisciplinary approaches to disaster risk reduction and the development of sustainable communities.

Allan, P., & Bryant, M. (2011b). Resilience as a framework for urbanism and recovery. *Journal of Landscape Architecture, 6*(2), 34-45.

Allan, P., & Bryant, M. (2014). The attributes of resilience: a tool in the evaluation and design of earthquake-prone cities. *International Journal of Disaster Resilience in the Built Environment, 5*(2), 109-129.

Allan, P., Bryant, M., Wirsching, C., Garcia, D., & Teresa Rodriguez, M. (2013). The influence of urban morphology on the resilience of cities following an earthquake. *Journal of Urban Design, 18*(2), 242-262.

Allenby, B., & Fink, J. (2005). Toward inherently secure and resilient societies. *Science, 309*(5737), 1034-1036.

Allison, P. D. (2014). *Measures of fit for logistic regression.* Paper presented at the Proceedings of the SAS Global Forum 2014 Conference.

Ananth, C. V., & Kleinbaum, D. G. (1997). Regression models for ordinal responses: a review of methods and applications. *International journal of epidemiology, 26*(6), 1323-1333.

Babbie, E. (2013). *The basics of social research*. Belmont, CA: Cengage Learning.

Babbie, E., & Rubin, A. (2008). Research methods for social work: Belmont, CA: Thompson Brooks/Cole.

Bagozzi, R. P., & Heatherton, T. F. (1994). A general approach to representing multifaceted personality constructs: application to state self-esteem. *Structural Equation Modeling: A Multidisciplinary Journal, 1*(1), 35-67.

Bahadur, A. V., & Thornton, H. (2015). Analysing urban resilience: a reality check for a fledgling canon. *International Journal of Urban Sustainable Development, 7*(2), 196-212.

Balsells, M., Becue, V., Barroca, B., Diab, Y., & Serre, D. (2011). Flood resilience assessment of New Orleans neighborhood over time. *Design Analysis in Rock Mechanics*, 151.

Batty, M. (2001). Polynucleated urban landscapes. *Urban Studies, 38*(4), 635-655.

Beaudry, C., & Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy, 38*(2), 318-337.

Beeton, R. (2006). Society's forms of capital: a framework for renewing our thinking. Paper prepared for the 2006 Australian State of the Environment Committee, Department of the Environment and Heritage, Canberra. *Department of the Environment and Heritage, Canberra*.

Bergen, S. D., Bolton, S. M., & Fridley, J. L. (2001). Design principles for ecological engineering. *Ecological Engineering, 18*(2), 201-210.

Berke, P., & Campanella, T. (2006). Planning for Postdisaster Resiliency. *Annals of the American Academy of Political and Social Science, 604*, 192-207.

Berke, P., & Smith, G. (2009). Hazard mitigation, planning, and disaster resiliency: Challenges and strategic choices for the 21st century. *Building Safer Communities. Risk Governance, Spatial Planning and Responses to Natural Hazards, 1*, 18.

Berke, P. R., Song, Y., & Stevens, M. (2009). Integrating hazard mitigation into new urban and conventional developments. *Journal of Planning Education and Research, 28*(4), 441-455.

Bevington, J., Hill, A., Davidson, R., Chang, S., Vicini, A., Adams, B., & Eguchi, R. (2011). *Measuring, monitoring and evaluating post-disaster recovery: A key element in understanding community resilience.* Paper presented at the ASCE Structures Congress.

Bird, D., Box, P., Okada, T., Haynes, K., & King, D. (2013a). Response, recovery and adaptation in flood-affected communities in Queensland and Victoria.

Bird, D., King, D., Haynes, K., Box, P., Okada, T., & Nairn, K. (2013b). Impact of the 2010/11 floods and the factors that inhibit and enable household adaptation strategies. *Report for the National Climate Change Adaptation Research Facility. Gold Coast, Australia*.

Birkmann, J. (2006). Measuring vulnerability to promote disaster-resilient societies: Conceptual frameworks and definitions. *Measuring vulnerability to natural hazards: Towards disaster resilient societies*, 9-54.

Bolin, R. C. (1994). *Household and community recovery after earthquakes*: Institute of Behavioral Science University of Colorado.

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological bulletin, 110*(2), 305.

Borden, K. A., Schmidtlein, M. C., Emrich, C. T., Piegorsch, W. W., & Cutter, S. L. (2007). Vulnerability of US cities to environmental hazards. *Journal of Homeland Security and Emergency Management, 4*(2).

Boyd, E., Osbahr, H., Ericksen, P. J., Tompkins, E. L., Lemos, M. C., & Miller, F. (2008). Resilience and 'climatizing'development: examples and policy implications. *Development, 51*(3), 390-396.

Briassoulis, H. (2001). Sustainable development and its indicators: through a (planner's) glass darkly. *Journal of Environmental Planning and Management, 44*(3), 409-427.

Briggs, S. R., & Cheek, J. M. (1986). The role of factor analysis in the development and evaluation of personality scales. *Journal of personality, 54*(1), 106-148.

Briguglio, L., Cordina, G., Farrugia, N., & Vella, S. (2009). Economic vulnerability and resilience: concepts and measurements. *Oxford development studies, 37*(3), 229-247.

Brody, S. D., Gunn, J., Peacock, W., & Highfield, W. E. (2011). Examining the influence of development patterns on flood damages along the Gulf of Mexico. *Journal of Planning Education and Research*.

Brown, D., Platt, S., & Bevington, J. (2010). Disaster Recovery Indicators: guidelines for monitoring and evaluation. *CURBE, Cambridge University Centre for Risk in the Built Environment*.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake spectra, 19*(4), 733-752.

Brunner, M., & SÜβ, H.-M. (2005). Analyzing the reliability of multidimensional measures: An example from intelligence research. *Educational and Psychological Measurement, 65*(2), 227-240.

Bryant, F. B. (2000). Assessing the validity of measurement. In L. G. G. P. R. Yarnold (Ed.), *Reading and understanding MORE multivariate statistics* (pp. 99-146). Washington, DC, US: American Psychological Association.

Buckle, P., Mars, G., & Smale, S. (2000). New approaches to assessing vulnerability and resilience.

Burby, R., Deyle, R., Godschalk, D., & Olshansky, R. (2000). Creating Hazard Resilient Communities through Land-Use Planning. *Natural Hazards Review, 1*(2), 99-106. doi:doi:10.1061/(ASCE)1527-6988(2000)1:2(99)

Burton, C. G. (2012). *The development of metrics for community resilience to natural disasters.* (PhD dissertation), Univeristy of South Carolina, Columbia, SC.

Campanella, T. (2006). *Making resilient cities: Some axioms of urban resilience.* Paper presented at the 2006 Xi'an International Conference of Architecture and Technology, Proceedings.

Carmines, E. G., & Zeller, R. A. (1979). *Reliability and validity assessment* (Vol. 17): Sage publications.

Carpenter, A. (2014). Resilience in the social and physical realms: Lessons from the Gulf Coast. *International Journal of Disaster Risk Reduction*.

Carpenter, A. (2015). Resilience in the social and physical realms: Lessons from the Gulf Coast. *International Journal of Disaster Risk Reduction, 14, Part 3*, 290-301. doi:http://dx.doi.org/10.1016/j.ijdrr.2014.09.003

Carpenter, A. M. (2013a). *Resilience in the Social and Physical Realms: Lessons from the Gulf Coast.* Georgia Institute of Technology.

Carpenter, S., Walker, B., Anderies, J. M., & Abel, N. (2001). From metaphor to measurement: resilience of what to what? *Ecosystems, 4*(8), 765-781.

Carpenter, S. R. (2013b). Complex systems: Spatial signatures of resilience. *Nature, 496*(7445), 308-309.

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate behavioral research, 1*(2), 245-276.

Chakrabarti, V. (2013). How Density makes Us Safer During Natural Disasters. Retrieved from http://www.citylab.com/housing/2013/09/how-density-makes-us-safer-during-natural-disasters/6864/

Chambers, R., & Conway, G. (1992). *Sustainable rural livelihoods: practical concepts for the 21st century*: Institute of Development Studies (UK).

Chang, S. E. (2010). Urban disaster recovery: a measurement framework and its application to the 1995 Kobe earthquake. *Disasters, 34*(2), 303-327.

Chang, S. E., & Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. *Earthquake spectra, 20*(3), 739-755.

Chang, Y., Wilkinson, S., Seville, E., & Potangaroa, R. (2010). Resourcing for a resilient post-disaster reconstruction environment. *International Journal of Disaster Resilience in the Built Environment, 1*(1), 65-83.

Chelleri, L. (2012). From the «Resilient City» to Urban Resilience. A review essay on understanding and integrating the resilience perspective for urban systems. *Documents d'anàlisi geogràfica, 58*(2), 287-306.

Cheng, S., Ganapati, E., & Ganapati, S. (2015). Measuring disaster recovery: bouncing back or reaching the counterfactual state? *Disasters*.

Churchill Jr, G. A. (1979). A paradigm for developing better measures of marketing constructs. *Journal of marketing research*, 64-73.

Cimellaro, G. P., Renschler, C., Frazier, A., Arendt, L., Bruneau, M., & Reinhorn, A. (2011). Community resilience index for road network systems.

Clark, G. E., Moser, S. C., Ratick, S. J., Dow, K., Meyer, W. B., Emani, S., . . . Schwarz, H. E. (1998). Assessing the vulnerability of coastal communities to extreme storms: the case of Revere, MA., USA. *Mitigation and adaptation strategies for global change, 3*(1), 59-82.

Coaffee, J. (2008). Risk, resilience, and environmentally sustainable cities. *Energy Policy, 36*(12), 4633-4638. doi:http://dx.doi.org/10.1016/j.enpol.2008.09.048

Collier, M. J., Nedović-Budić, Z., Aerts, J., Connop, S., Foley, D., Foley, K., . . . Verburg, P. (2013). Transitioning to resilience and sustainability in urban communities. *Cities, 32, Supplement 1*, S21-S28. doi:http://dx.doi.org/10.1016/j.cities.2013.03.010

Coltman, T., Devinney, T. M., Midgley, D. F., & Venaik, S. (2008). Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business Research, 61*(12), 1250-1262.

Comerio, M., & Blecher, H. (2010). *Downtime data on residential buildings after the Northridge and Loma Prieta earthquakes.* Paper presented at the Earthquake Engineering Research Institute (ed.) Proceedings of the Ninth US National and Tenth Canadian Conference on Earthquake Engineering. Toronto, Canada.

Comerio, M. C. (1998). *Disaster hits home: New policy for urban housing recovery*: Univ of California Press.

Comerio, M. C. (2006). Estimating downtime in loss modeling. *Earthquake spectra, 22*(2), 349-365.

Comfort, L., Wisner, B., Cutter, S., Pulwarty, R., Hewitt, K., Oliver-Smith, A., . . . Krimgold, F. (1999). Reframing disaster policy: the global evolution of vulnerable communities. *Global Environmental Change Part B: Environmental Hazards, 1*(1), 39-44.

Council of Australian Governments. (2011). *National strategy for disaster resilience: Building the resilience of our nation to disasters*. Retrieved from

Cox, T. F., & Cox, M. A. (2000). *Multidimensional scaling*: CRC Press.

Crawford, K., Kranzberg, M., & Bowker, G. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society, 15*(5), 662-679.

Cronbach, L. J., Schönemann, P., & McKie, D. (1965). Alpha coefficients for Stratified-Parallel Tests. *Educational and Psychological Measurement*.

Cullen, A. C., & Frey, H. C. (1999). *Probabilistic techniques in exposure assessment: a handbook for dealing with variability and uncertainty in models and inputs*: Springer Science & Business Media.

Cumming, G. S., Barnes, G., Perz, S., Schmink, M., Sieving, K. E., Southworth, J., . . . Van Holt, T. (2005). An exploratory framework for the empirical measurement of resilience. *Ecosystems, 8*(8), 975-987.

Cutter, S., Boruff, B. J., & Shirley, W. L. (2006). Social Vulnerability to Environmental Hazards. *Hazards, Vulnerability, and Environmental Justice*, 115-132.

Cutter, S. L. (1996). Societal responses to environmental hazards. *International Social Science Journal, 48*(150), 525-536.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global environmental change, 18*(4), 598-606.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards*. *Social Science Quarterly, 84*(2), 242-261.

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. *Journal of Homeland Security and Emergency Management, 7*(1).

da Silva, J., Moench, M., Tyler, S., & Kernaghan, S. (2010). Urban Resilience Framework. *Arup/ISET working document for ACCCRN program. Forthcoming*.

Dalziell, E., & McManus, S. (2004). Resilience, vulnerability, and adaptive capacity: implications for system performance.

Davidson, R. A., & Shah, H. C. (1997). *An urban earthquake disaster risk index*: John A. Blume Earthquake Engineering Center Standford University.

Davoudi, S., Shaw, K., Haider, L. J., Quinlan, A. E., Peterson, G. D., Wilkinson, C., . . . Davoudi, S. (2012). Resilience: A Bridging Concept or a Dead End?"Reframing" Resilience: Challenges for Planning Theory and Practice Interacting Traps. *Planning Theory & Practice, 13*(2), 299-333.

Deppisch, S., & Schaerffer, M. (2011). Given the Complexity of Large Cities, Can Urban Resilience be Attained at All? *German Annual of Spatial Research and Policy 2010* (pp. 25-33): Springer.

Dimitrov, D. M. (2014). *Statistical methods for validation of assessment scale data in counseling and related fields*: John Wiley & Sons.

Drupsteen, L., & Guldenmund, F. W. (2014). What is learning? A review of the safety literature to define learning from incidents, accidents and disasters. *Journal of Contingencies and Crisis Management, 22*(2), 81-96.

Dynes, R. R. (2002). *The importance of social capital in disaster response*: University of Delaware, Disaster Research Center Newark, DE.

Dynes, R. R. (2005). Community social capital as the primary basis for resilience. *University of Delaware Disaster Research Centre Preliminary paper*.

Eraydin, A., & Taşan-Kok, T. (2013). Introduction: Resilience Thinking in Urban Planning *Resilience Thinking in Urban Planning* (pp. 1-16): Springer.

Eves, C. (2011). *Tracking the short term impact of floods on residential property markets*. Retrieved from: http://eprints.qut.edu.au/69637/3/69637a.pdf

Eves, C., & Wilkinson, S. (2014). Assessing the immediate and short-term impact of flooding on residential property participant behaviour. *Natural hazards, 71*(3), 1519-1536.

Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards and Earth System Science, 9*(2), 393-403.

Finch, C., Emrich, C. T., & Cutter, S. L. (2010). Disaster disparities and differential recovery in New Orleans. *Population and Environment, 31*(4), 179-202.

Fletcher, R. (2013). *Practical methods of optimization*: John Wiley & Sons.

Flyvbjerg, B. (2006). Five misunderstandings about case-study research. *Qualitative inquiry, 12*(2), 219-245.

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global environmental change, 16*(3), 253-267.

Fornell, C., Tellis, G. J., & Zinkhan, G. M. (1982). *Validity assessment: A structural equations approach using partial least squares.* Paper presented at the proceedings, American Marketing Association Educators' conference.

Foster, H. D. (1993). Resilience theory and system evaluation *Verification and Validation of Complex Systems: Human Factors Issues* (pp. 35-60): Springer.

Fothergill, A., Maestas, E. G., & Darlington, J. D. (1999). Race, ethnicity and disasters in the United States: A review of the literature. *Disasters, 23*(2), 156-173.

Fox, J. (2000). *Nonparametric simple regression: smoothing scatterplots*: Sage.

Frankenberger, T., Langworthy, M., Spangler, T., Nelson, S., Campbell, J., & Njoka, J. (2012). Enhancing Resilience to Food Security Shocks. *White Paper (Draft). TANGO International, Tucson*.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional studies, 41*(5), 685-697.

Freudenberg, M. (2003). Composite Indicators of Country Performance: a critical assessment, OECD, Paris.

Füssel, H.-M. (2010). Review and quantitative analysis of indices of climate change exposure, adaptive capacity, sensitivity, and impacts.

Gall, M. (2007). *Indices of social vulnerability to natural hazards: a comparative evaluation*: ProQuest.

Gall, M. (2013). *From social vulnerability to resilience: measuring progress toward disaster risk reduction*: UNU-EHS.

Gallopín, G. C. (2006). Linkages between vulnerability, resilience, and adaptive capacity. *Global Environmental Change, 16*(3), 293-303.

Geis, D., & Kutzmark, T. (1995). Development sustainable communities *Public Management* (pp. 4-13).

GFDRR. (2015). *Guide to developing disaster recovery frameworks*. Paper presented at the Sendai Conference, Japan. https://www.gfdrr.org/sites/gfdrr/files/publication/DRF-Guide.pdf

Gilbert, S. W. (2010). Disaster resilience: A guide to the literature. *NIST Special Publication, 1117*.

Godschalk, D. (1999). *Natural hazard mitigation: Recasting disaster policy and planning*: Island Press.

Godschalk, D. R. (2003). Urban hazard mitigation: creating resilient cities. *Natural Hazards Review, 4*(3), 136-143.

Godschalk, D. R., Kaiser, E. J., & Berke, P. R. (1998). Integrating hazard mitigation and local land use planning. *Cooperating with nature: Confronting natural hazards with land-use planning for sustainable communities*, 85-118.

Goertz, G. (2006). *Social science concepts: A user's guide*: Princeton University Press.

Queensland Floods Commision of Inquiry. (2011). *Rebuilding a stronger, more resilient Queensland*. Retrieved from: http://qldreconstruction.org.au/u/lib/cms2/rebuilding-resilient-qld-full.pdf

Green, G. P., Haines, A., Dunn, A., & Sullivan, D. M. (2002). The Role of Local Development Organizations in Rural America*. *Rural Sociology, 67*(3), 394-415.

Guba, E. G., & Lincoln, Y. S. (1994). Competing paradigms in qualitative research. *Handbook of qualitative research, 2*(163-194).

Guillaumont, P. (2008). *An economic vulnerability index: its design and use for international development policy*: Research paper/UNU-WIDER.

Gunderson, L. (2010). Ecological and human community resilience in response to natural disasters. *Ecology and Society, 15*(2), 18.

Gunderson, L. H. (2000). Ecological resilience--in theory and application. *Annual review of ecology and systematics*, 425-439.

Haigh, R., & Amaratunga, D. (2010). An integrative review of the built environment discipline's role in the development of society's resilience to disasters. *International Journal of Disaster Resilience in the Built Environment, 1*(1), 11-24.

Haimes, Y. Y., Crowther, K., & Horowitz, B. M. (2008). Homeland security preparedness: Balancing protection with resilience in emergent systems. *Systems Engineering, 11*(4), 287-308.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (Vol. 6): Pearson Prentice Hall Upper Saddle River, NJ.

Hambleton, R. (2015). *Beyond resilience: The role of leadership in progressive planning*. Paper presented at the Association of European Schools of Planninig (AESOP), Prague, Czech Republic.

Heinz, H. J. (2000). *The hidden costs of coastal hazards: Implications for risk assessment and mitigation*: Island Press.

Hezri, A. A., & Dovers, S. R. (2006). Sustainability indicators, policy and governance: issues for ecological economics. *Ecological Economics, 60*(1), 86-99.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual review of ecology and systematics*, 1-23.

Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems, 4*(5), 390-405.

Holmes, C. E. (2012). *Queensland Floods Commission of Inquiry: Final Report*: Queensland Floods Commission of Inquiry.

Hurlimann, A. C., & March, A. P. (2012). The role of spatial planning in adapting to climate change. *Wiley Interdisciplinary Reviews: Climate Change, 3*(5), 477-488.

Irajifar, L., Alizadeh, T., & Sipe, N. (2013). *Disaster resiliency measurement frameworks: State of the art.* Paper presented at the World Building Congress, Brisbane, Australia.

Izraeli, O., & Murphy, K. J. (2003). The effect of industrial diversity on state unemployment rate and per capita income. *The Annals of Regional Science, 37*(1), 1-14.

Jacobs, P., Smith, P., & Goddard, M. (2004). The Development of Composite Indicators to Measure Performance in Health Care. *Performance Measurement and Management: Public and Private. A. Walters. Edinburgh, UK, Centre for Business Performance, 1*, 491-498.

Jenks, G. F., & Caspall, F. C. (1971). Error on choroplethic maps: definition, measurement, reduction. *Annals of the Association of American Geographers, 61*(2), 217-244.

Jenks, M., & Jones, C. (2009). *Dimensions of the sustainable city* (Vol. 2): Springer Science & Business Media.

Jha, A. K., Miner, T. W., & Stanton-Geddes, Z. (2013). *Building urban resilience: Principles, tools, and practice*. World Bank Publications. Washington.

Johansson, R. (2003). *Case study methodology.* Paper presented at the the International Conference on Methodologies in Housing Research, Stockholm.

Jolliffe, I. (2002). *Principal component analysis*: Wiley Online Library.

Jordan, E., & Javernick-Will, A. (2013). Indicators of community recovery: content analysis and Delphi approach. *Natural hazards review*.

Jordan, E., & Javernick-Will, A. (2014). Determining Causal Factors of Community Recovery. *International Journal of Mass Emergencies & Disasters, 32*(3).

Jordan, E., Javernick-Will, A., & Amadei, B. (2014). A qualitative comparative analysis of neighborhood recovery following Hurricane Katrina. *International Journal of Disaster Resilience in the Built Environment, 5*(4), 391-412.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31-36.

Kamata, A., Turhan, A., & Darandari, E. (2003). *Estimating reliability for multidimensional composite scale scores.* Paper presented at the annual meeting of American Educational Research Association, Chicago, IL.

Kärrholm, M., Nylund, K., & de la Fuente, P. P. (2014). Spatial resilience and urban planning: Addressing the interdependence of urban retail areas. *Cities, 36*, 121-130.

Kates, R. W., Colten, C. E., Laska, S., & Leatherman, S. P. (2006). Reconstruction of New Orleans after Hurricane Katrina: a research perspective. *Proceedings of the National Academy of Sciences, 103*(40), 14653-14660.

Khailani, D. K., & Perera, R. (2013). Mainstreaming disaster resilience attributes in local development plans for the adaptation to climate change induced flooding: A study based on the local plan of Shah Alam City, Malaysia. *Land Use Policy, 30*(1), 615-627.

King, D., Bird, D., Haynes, K., Boon, H., Cottrell, A., Millar, J., . . . Thomas, M. (2014). Voluntary relocation as an adaptation strategy to extreme weather events. *International Journal of Disaster Risk Reduction, 8*, 83-90.

Klein, R. J., Nicholls, R. J., & Thomalla, F. (2003). Resilience to natural hazards: How useful is this concept? *Global Environmental Change Part B: Environmental Hazards, 5*(1), 35-45.

Kruskal, J. B. (1964). Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika, 29*(1), 1-27.

Kruskal, J. B., & Wish, M. (1978). *Multidimensional scaling* (Vol. 11): Sage.

Lall, S. V., & Deichmann, U. (2011). Density and disasters: economics of urban hazard risk. *The World Bank Research Observer*.

Lall, S. V., & Deichmann, U. (2012). Density and disasters: economics of urban hazard risk. *The World Bank Research Observer, 27*(1), 74-105.

Law, K. S., Wong, C.-S., & Mobley, W. M. (1998). Toward a taxonomy of multidimensional constructs. *Academy of management review, 23*(4), 741-755.

Leichenko, R. (2011). Climate change and urban resilience. *Current opinion in environmental sustainability, 3*(3), 164-168.

Liepmann, D., & Stephanopoulos, G. (1985). A dynamic model of a closed ecosystem: development and global sensitivity analysis. *Ecological Modelling, 30*, 13-30.

Lindell, M. K., & Prater, C. S. (2003). Assessing community impacts of natural disasters. *Natural hazards review, 4*(4), 176-185.

Little, R. G. (2003). *Toward more robust infrastructure: observations on improving the resilience and reliability of critical systems.* Paper presented at the System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference on.

Liu, A., Fellowes, M., & Mabanta, M. (2006). *Special edition of the Katrina index: A one year review of key indicators of recovery in post-storm New Orleans*: Brookings Institution.
Lo, A. Y. (2013). Household Preference and Financial Commitment to Flood Insurance in South-East Queensland. *Australian Economic Review, 46*(2), 160-175.
Longstaff, P. H., Armstrong, N. J., Perrin, K., Parker, W. M., & Hidek, M. (2010). Building resilient communities a preliminary framework for assessment.
MacKenzie, S. B., Podsakoff, P. M., & Jarvis, C. B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology, 90*(4), 710-730.
MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS quarterly, 35*(2), 293-334.
Maguire, B., & Hagan, P. (2007). Disasters and communities: understanding social resilience. *Australian Journal of Emergency Management, 22*(2), 16-20.
Malalgoda, C., Amaratunga, D., & Haigh, R. (2013). Creating a disaster resilient built environment in urban cities: The role of local governments in Sri Lanka. *International Journal of Disaster Resilience in the Built Environment, 4*(1), 72-94.
Manyena, S. B. (2006). The concept of resilience revisited. *Disasters, 30*(4), 434-450.
Manyena, S. B., & Gordon, S. (2015). Bridging the concepts of resilience, fragility and stabilisation. *Disaster Prevention and Management, 24*(1), 38-52.
March, A., Holland, M., & Harwood, A. (2011). Planning for Bushfire Resilient Urban Design. *State of Australian Cities National*.
Mason, M. S., Phillips, E., Okada, T., & O'Brien, J. (2012). Analysis of damage to buildings following the 2010–11 Eastern Australia floods.
Mathbor, G. M. (2007). Enhancement of community preparedness for natural disasters the role of social work in building social capital for sustainable disaster relief and management. *International Social Work, 50*(3), 357-369.
Mayada, O. (2011). *Defining and measuring the resiliency of networked infrastructure systems.* (PhD), Stevenson Institute of Technology, New York.
Mayunga, J. S. (2007). Understanding and applying the concept of community disaster resilience: a capital-based approach. *Summer academy for social vulnerability and resilience building, 1*, 16.
Mayunga, J. S. (2009). *Measuring the measure: A multi-dimensional scale model to measure community disaster resilience in the US Gulf Coast region.* Texas A&M University.
McCarthy, K., & Hanson, M. (2008). Technical report: Post-Katrina recovery of the housing market along the Mississippi Gulf coast: Santa Monica, California: RAND Corporation, Gulf States Policy Institute.
Meerow, S., Newell, J. P., & Stults, M. (2016). Defining urban resilience: A review. *Landscape and Urban Planning, 147*, 38-49. doi:http://dx.doi.org/10.1016/j.landurbplan.2015.11.011
Meredith, J. (1993). Theory building through conceptual methods. *International Journal of Operations & Production Management, 13*(5), 3-11.
Middelmann, M. H. (2007). *Natural hazards in Australia: Identifying risk analysis requirements* (1921236604). Retrieved from: https://d28rz98at9flks.cloudfront.net/65444/65444.pdf
Miles, S., & Chang, S. (2008). *ResilUS--Modeling Community Capital Loss and Recovery.* Paper presented at the The 14th World Conference on Earthquake Engineering.
Miles, S. B., & Chang, S. E. (2003). Urban disaster recovery: A framework and simulation model.
Miles, S. B., & Chang, S. E. (2011). ResilUS: a community based disaster resilience model. *Cartography and Geographic Information Science, 38*(1), 36-51.
Mileti, D. (1999). *Disasters by Design:: A Reassessment of Natural Hazards in the United States*: Joseph Henry Press.

Miller, F., Osbahr, H., Boyd, E., Thomalla, F., Bharawani, S., Ziervogel, G., . . . Rockström, J. (2010). Resilience and vulnerability: complementary or conflicting concepts? *Ecology and Society, 15*(3).

Mitchell, A. (2013). Risk and Resilience - From Good Idea to Good Practice. *OECD, Paris*.

Mizuno, K., Mizutani, F., & Nakayama, N. (2006). Industrial diversity and metropolitan unemployment rate. *The Annals of Regional Science, 40*(1), 157-172.

Morrow, B. H. (1999). Identifying and mapping community vulnerability. *Disasters, 23*(1), 1-18.

Müller, B. (2011). Urban and regional resilience–A new catchword or a consistent concept for research and practice? *German Annual of Spatial Research and Policy 2010* (pp. 1-13): Springer.

Munich Re Group. (2009). Natural disasters 1980–2008, 10 costliest typhoons ordered by insured losses. *Munich Re Group, Munich. Accessed 28th April http://www. munichre. com*.

Nardo, M., Saisana, M., Saltelli, A. and Tarantola, S. (2008). *Handbook on Constructing Composite Indicators : Methodology and user guide*. Paris, France: OECD publications.

National Emergency Management Committee. (2009). National Strategy for Disaster Resilience: Building our nation's resilience to disasters: Canberra: COAG.

Neter, J., Wasserman, W., & Kutner, M. (1990). Applied linear statistical models: regression, analysis of variance, and experimental designs. Chicago: Irwin.

Nicoletti, G., Scarpetta, S., & Boylaud, O. (2000). Summary indicators of product market regulation with an extension to employment protection legislation. *OECD Working Paper, No. 226*(Institutional Change).

Norman, S. (2006). New Zealand's holistic framework for disaster recovery. *Australian Journal of Emergency Management, The, 21*(4), 16.

Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American journal of community psychology, 41*(1-2), 127-150.

Nunnally, J. C., Bernstein, I. H., & Berge, J. M. t. (1967). *Psychometric theory* (Vol. 226): JSTOR.

Okuyama, Y. (2008). Critical review of Methodologies on disaster impacts estimation. *Background paper for EDRR report*.

Olshansky, R. B. (2005). *How do communities recover from disaster? A review of current knowledge and an agenda for future research.* Paper presented at the 46th Annual Conference of the Association of Collegiate Schools of Planning. Kansas City, MO.

Olshansky, R. B., Johnson, L. A., Horne, J., & Nee, B. (2008). Longer view: Planning for the rebuilding of New Orleans. *Journal of the American Planning Association, 74*(3), 273-287.

Olshansky, R. B., Johnson, L. A., & Topping, K. C. (2005). *Opportunity in Chaos: Rebuilding After the 1994 Northridge and 1995 Kobe Earthquakes*. San Francisco. Retrieved from: https://nees.org/announcements/oacrebuilingavailable.

Pais, J. F., & Elliott, J. R. (2008). Places as Recovery Machines: Vulnerability and Neighborhood Change After Major Hurricanes. *Social Forces, 86*(4), 1415-1453. doi:10.1353/sof.0.0047

Paton, D., & Johnston, D. (2001). Disasters and communities: vulnerability, resilience and preparedness. *Disaster Prevention and Management: An International Journal, 10*(4), 270-277.

Pelling, M. (2003). The Vulnerability of Cities: social resilience and natural disaster. *London: Earthscan*, 212.

Perry, C. (1998). Processes of a case study methodology for postgraduate research in marketing. *European journal of marketing, 32*(9/10), 785-802.

Pickett, S. T., Cadenasso, M. L., & Grove, J. M. (2004). Resilient cities: meaning, models, and metaphor for integrating the ecological, socio-economic, and planning realms. *Landscape and Urban Planning, 69*(4), 369-384.

Pierce, J., Budd, W., & Lovrich Jr, N. (2011). Resilience and sustainability in US urban areas. *Environmental Politics, 20*(4), 566-584.

Pike, A., Dawley, S., & Tomaney, J. (2010). Resilience, adaptation and adaptability. *Cambridge Journal of Regions, Economy and Society*.
Putnam, R. (2001). Social capital: Measurement and consequences. *Canadian Journal of Policy Research, 2*(1), 41-51.
Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*: Wiley Online Library.
Ragin, C. C., Drass, K. A., & Davey, S. (2006). Fuzzy-set/qualitative comparative analysis 2.0. *Tucson, Arizona: Department of Sociology, University of Arizona*.
Ragin, C. C., Rubinson, C., Schaefer, D., Anderson, S., Williams, E., & Giesel, H. (2008). User's guide to fuzzy-set/qualitative comparative analysis. *University of Arizona, 87*.
Rambaldi, A., & Rao, D. (2011). *The effect of hedonic modeling and index weights on hedonic imputation indexes.* Paper presented at the 31st General Conference of The International Association for Research in Income and Wealth.
Ranger, J., & Kuhn, J. T. (2012). Assessing fit of item response models using the information matrix test. *Journal of Educational Measurement, 49*(3), 247-268.
Raykov, T. (1998). Coefficient alpha and composite reliability with interrelated nonhomogeneous items. *Applied psychological measurement, 22*(4), 375-385.
Renschler, C., Frazier, A., Arendt, L., Cimellaro, G. P., Reinhorn, A., & Bruneau, M. (2010). *Developing the 'PEOPLES'resilience framework for defining and measuring disaster resilience at the community scale.* Paper presented at the Proceedings of the 9th US national and 10th Canadian conference on earthquake engineering (9USN/10CCEE), Toronto.
Renschler, C., Reinhorn, A. M., Arendt, L., & Cimellaro, G. P. (2011). *The PEOPLES Resilience Framework: A conceptual approach to quantify community resilience.* Paper presented at the Proceedings of the 3rd international conference on Computational Methods in Structural Dynamics and Earthquake Engineering (COMPDYN 2011), Corfu.
Renschler, C. S. (2013). The PEOPLES Resilience Framework–An Integrated Quantitative Measure and Modeling of Sustainable Development and Disaster Risk Reduction.
Renski, H. (2011). External economies of localization, urbanization and industrial diversity and new firm survival. *Papers in Regional Science, 90*(3), 473-502.
Resilient Design Principles. (2012). Design Priciples for Creating more Resilient Cities. Retrieved from http://www.resilientcity.org/index.cfm?id=11900
Rivera, F. I., & Settembrino, M. R. (2010). Toward a Sociological Framework of Community Resilience.
Rose, A. (2004). Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal, 13*(4), 307-314.
Rose, A. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards, 7*(4), 383-398.
Rose, A. (2011). Resilience and sustainability in the face of disasters. *Environmental Innovation and Societal Transitions, 1*(1), 96-100.
Rose, A., & Krausmann, E. (2013). An economic framework for the development of a resilience index for business recovery. *International Journal of Disaster Risk Reduction, 5*, 73-83.
Rubin, C. B., Saperstein, M. D., & Barbee, D. G. (1985). Community recovery from a major natural disaster.
Rubinoff, P., & Courtney, C. (2007). How Resilient is Your Coastal Community? A Guide for Evaluating Coastal Community Resilience to Tsunamis and Other Coastal Hazards: USAID-ASIA, Bangkok, Thailand.
Sadler, S. (2005). *Archigram: architecture without architecture*: MIT Press.
Saisana, M., Saltelli, A., & Tarantola, S. (2005). Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 168*(2), 307-323.
Salat, S., Bourdic, L., & Nowacki, C. (2010a). Assessing urban complexity. *International Journal of Sustainable Building Technology and Urban Development, 1*(2), 160-167.

Salat, S., Vialan, D., & Nowacki, C. (2010b). *A common metrics and set of indicators for assessing buildings and urban fabric sustainability performance*. Paper presented at the Central Europe towards Sustainable Building, Prague.

Saltelli, A., Nardo, M., Saisana, M., & Tarantola, S. (2005). Composite indicators: the controversy and the way forward, OECD World Forum on Key Indicators, Plermo, 10-13 November.

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing" neighborhood effects": Social processes and new directions in research. *Annual review of sociology*, 443-478.

Schilling, T. A. (2008). An examination of resilience processes in context: The case of Tasha. *The Urban Review, 40*(3), 296-316.

Schipper, E. L. F., & Langston, L. (2015). A comparative overview of resilience measurement frameworks. ODI. Retrieved from: http://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/9754.pdf.

Schmidtlein, M. C., Deutsch, R. C., Piegorsch, W. W., & Cutter, S. L. (2008). A sensitivity analysis of the social vulnerability index. *Risk Analysis, 28*(4), 1099-1114.

Schneiderbauer, S., & Ehrlich, D. (2006). Social levels and hazard (in) dependence in determining vulnerability. *Measuring vulnerability to natural hazards: Towards disaster resilient societies*, 78-102.

Seto, K. C., Sánchez-Rodríguez, R., & Fragkias, M. (2010). The new geography of contemporary urbanization and the environment. *Annual review of environment and resources, 35*, 167-194.

Shaw, R., & Team, I. (2009). Climate disaster resilience: focus on coastal urban cities in Asia. *Asian Journal of Environment and Disaster Management, 1*, 101-116.

Sherrieb, K., Norris, F. H., & Galea, S. (2010). Measuring capacities for community resilience. *Social Indicators Research, 99*(2), 227-247.

Simpson, D. M., & Katirai, M. (2006). Indicator issues and proposed framework for a disaster preparedness index (DPi). *University of Louisville*.

Simpson, E. H. (1949). Measurement of diversity. *Nature*. 163: 688.

Sireci, S. G. (2007). On validity theory and test validation. *Educational Researcher, 36*(8), 477-481.

Smith, G. P., & Wenger, D. (2007). Sustainable disaster recovery: operationalizing an existing agenda *Handbook of disaster research* (pp. 234-257): Springer.

Smith, R., Simard, C., & Sharpe, A. (2001). A proposed approach to environment and sustainable development indicators based on capital. *A report prepared for the National Round Table on the Environment and the Economy's Environment and Sustainable Development Indicators Initiative*.

Solomon, S. (2007). *IPCC (2007): Climate Change The Physical Science Basis.* Paper presented at the AGU Fall Meeting Abstracts.

Sterbenz, J. P., Cetinkaya, E. K., Hameed, M. A., Jabbar, A., & Rohrer, J. P. (2011). *Modelling and analysis of network resilience.* Paper presented at the Communication Systems and Networks (pp. 1-10). IEEE.

Stevens, M. R., Berke, P. R., & Song, Y. (2010). Creating disaster-resilient communities: Evaluating the promise and performance of new urbanism. *Landscape and Urban Planning, 94*(2), 105-115. doi:http://dx.doi.org/10.1016/j.landurbplan.2009.08.004

Stevenson, J. R., Emrich, C. T., Mitchell, J. T., & Cutter, S. L. (2010). Using building permits to monitor disaster recovery: A spatio-temporal case study of coastal Mississippi following Hurricane Katrina. *Cartography and Geographic Information Science, 37*(1), 57-68.

Stumpp, E.-M. (2013). New in town? On resilience and “Resilient Cities”. *Cities, 32*, 164-166.

Tabachnick, B. G., & Fidell, L. S. (1996). *SPSS for Windows Workbook to Accompany Large Sample Examples of Using Multivariate Statistics*: HarperCollins College Publishers.

Tate, E. (2012). Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. *Natural hazards, 63*(2), 325-347.

Tierney , e. a. (2007). Conceptualizing and measuring resilience: A key to disaster loss reduction. *TR News,* 14-17.

Tierney, K. (2009). *Disaster response: Research findings and their implications for resilience measures*. CARRI Research Report.

Timmerman, P. (1981). Vulnerability resilience and collapse ofsociety. *A ReviewofModels and Possible Climatic Appli-cations. Toronto, Canada. Institute for Environmental Studies, University of Toronto*.

Tobin, G. A. (1999). Sustainability and community resilience: the holy grail of hazards planning? *Global Environmental Change Part B: Environmental Hazards, 1*(1), 13-25.

Tobin, G. A., & Whiteford, L. M. (2002). Community resilience and volcano hazard: the eruption of Tungurahua and evacuation of the faldas in Ecuador. *Disasters, 26*(1), 28-48.

Tyler, S., Nugraha, E., Nguyen, H. K., Van Nguyen, N., Sari, A. D., Thinpanga, P., . . . Bizikova, L. (2014). *Developing Indicators of Urban Climate Resilience*. ISET Climate Resilience.

Tyler, S., Reed, S. O., MacClune, K., & Chopde, S. (2010). Planning for Urban Climate Resilience; Framework and Examples from the Asian Cities Climate Change Resilience Network. *Climate Resilience in Concept and Practice Working Paper Series*.

Uday, P., & Marais, K. (2015). Designing Resilient Systems-of-Systems: A Survey of Metrics, Methods, and Challenges. *Systems Engineering*. 18(5), 491-510.

UNISDR. (2005). *Hyogo framework for action 2005-2015: building the resilience of nations and communities to disasters.* Extract from the final report of the World Conference on Disaster Reduction (A/CONF. 206/6).

Untermann, R., & Moudon, A. V. (1989). Street design; reassessing the safety, sociability, and economics of streets. *University of Washington, Department of Urban Planning, Seattle*, 3.

van den Honert, R. C., & McAneney, J. (2011). The 2011 Brisbane floods: causes, impacts and implications. *Water, 3*(4), 1149-1173.

Vincent, K. (2004). Creating an index of social vulnerability to climate change for Africa. *Tyndall Center for Climate Change Research. Working Paper, 56*, 41.

Walker, B., Gunderson, L., Kinzig, A., Folke, C., Carpenter, S., & Schultz, L. (2006). A handful of heuristics and some propositions for understanding resilience in social-ecological systems. *Ecology and Society, 11*(1), 13.

Walker, B., & Salt, D. (2012). *Resilience thinking: sustaining ecosystems and people in a changing world*: Island Press.

Wallace, D., & Wallace, R. (2008). Urban systems during disasters: factors for resilience. *Ecology and Society, 13*(1), 18.

Waller, M. A. (2001). Resilience in ecosystemic context: evolution of the concept. *American Journal of Orthopsychiatry, 71*(3), 290.

Walters, P. (2015). The problem of community resilience in two flooded cities: Dhaka 1998 and Brisbane 2011. *Habitat International, 50*, 51-56. doi:http://dx.doi.org/10.1016/j.habitatint.2015.08.004

Wardekker, J. A., de Jong, A., Knoop, J. M., & van der Sluijs, J. P. (2010). Operationalising a resilience approach to adapting an urban delta to uncertain climate changes. *Technological Forecasting and Social Change, 77*(6), 987-998.

Wegener, M. (1994). Operational urban models state of the art. *Journal of the American Planning Association, 60*(1), 17-29.

Wickes, R., Zahnow, R., Taylor, M., & Piquero, A. R. (2015). Neighborhood Structure, Social Capital, and Community Resilience: Longitudinal Evidence from the 2011 Brisbane Flood Disaster*. *Social Science Quarterly, 96*(2), 330-353.

Wildavsky, A. B. (1988). *Searching for safety* (Vol. 10): Transaction publishers.New Brunswich, NJ.

Wilkinson, C. (2012a). Social-ecological resilience: Insights and issues for planning theory. *Planning Theory, 11*(2), 148-169.

Wilkinson, C. (2012b). Urban resilience: What does it mean in planning practice. *Planning Theory and Practice, 13*(2), 319-324.
Winderl, T. (2015). Disaster resilience measurements: stocktaking of ongoing efforts in developing systems for measuring resilience. *UNDP http:// www. preventionweb. net/ files/ 37916_ disasterresilien cemeasurementsun dpt. pdf. Accessed, 25*.
Windle, G., Bennett, K. M., & Noyes, J. (2011). A methodological review of resilience measurement scales. *Health and quality of life outcomes, 9*(8), 1-18.
Wisner, B., Blaikie, P., Cannon, T., & Davis, I. (2004). At Risk: Natural Hazards. *People's Vulnerability and* Disasters, New York, NY, Routledge.
Wong, C. (2006). *Indicators for urban and regional planning: the interplay of policy and methods*. Oxon, UK. Routledge.
Woolcock, M., & Narayan, D. (2000). Social capital: Implications for development theory, research, and policy. The world bank research observer,15(2), 225-249.
Xiao, Y., & Drucker, J. (2013). Does economic diversity enhance regional disaster resilience? *Journal of the American Planning Association, 79*(2), 148-160.
Yin, R. K. (2013). *Case study research: Design and methods*: Sage publications.
Zhang, Y., & Peacock, W. G. (2009). Planning for housing recovery? Lessons learned from Hurricane Andrew. *Journal of the American Planning Association, 76*(1), 5-24.
Zhou, H., Wang, J. a., Wan, J., & Jia, H. (2010). Resilience to natural hazards: a geographic perspective. *Natural hazards, 53*(1), 21-41. doi:10.1007/s11069-009-9407-y
Zimmerman, R. (2001). Social implications of infrastructure network interactions. *Journal of Urban Technology, 8*(3), 97-119.

Appendix

This appendix provides the details of the QCA procedure for recovery pathway analysis. The truth tables, conditions, assumptions and outputs are also included.

Recovery Outcome 1: Housing reconstruction after 10 months

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 10 months = f (House price change, Damage loss, ~SoVI, %Not single family detached houses, Economic stability, Recovery funds)

Rows: 6

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.894592

	Raw Coverage	Unique Coverage	Consistency
~House price change*~Damage loss*~SoVI *%Not single family detached houses*Economic stability	0.36	0.16	0.95
~Damage loss*~SoVI*~%Not single family detached houses *Economic stability*Recovery funds	0.42	0.08	0.89
~House price change*~SoVI*~%Not single family detached houses *Economic stability*Recovery funds	0.40	0.06	0.90

Solution coverage: 0.648035

Solution consistency: 0.895975

Cases with greater than 0.5 memberships in term ~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability:

Yeerongpilly (0.611059, 0.951816), Sherwood (0.605781, 0.726897), Yeronga (0.563348, 0.779216), Moorooka (0.539871, 0.615067), Fairfield (0.532252, 0.750629), Tennyson (0.514187, 0.242898), Greenslopes (0.512054, 0.640417)

Cases with greater than 0.5 memberships in term ~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds:

Graceville (0.801634, 0.670622), Karalee (0.8, 1), Chelmer (0.766752, 0.748472), Barellan (0.7, 0), Kholo (0.685632, 0.790004), Mount Ommaney (0.59, 0.691837)

Cases with greater than 0.5 memberships in term ~House price change*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds:

Chelmer (0.710076, 0.748472), Barellan (0.638901, 0), Jindalee (0.601452, 0.550521), Oxley (0.561114, 0.730313), Karalee (0.536643, 1)

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 10 months = f (House price change, Damage loss, ~SoVI, %Not single family detached houses, Economic stability, Recovery funds)

Rows: 6

Algorithm: Quine-McCluskey

True: 1

--- PARSIMONIOUS SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.894592

	Raw Coverage	Unique Coverage	Consistency
Recovery funds	0.70	0.10	0.77
~Damage loss	0.84	0.25	0.73

Solution coverage: 0.943003

Solution consistency: 0.725519

Cases with greater than 0.5 memberships in term Recovery funds:

Jindalee (1,0.550521), Karalee (1,1), Tennyson (1,0.242898), Yeronga (1,0.779216), Barellan (0.92,0), Fairfield (0.85,0.750629), Riverview (0.85,1), Chelmer (0.83,0.748472), Graceville (0.83,0.670622), Kholo (0.77,0.790004), Goodna (0.73,0.0880978), Oxley (0.69,0.730313), Sherwood (0.67,0.726897), Redbank (0.62,0.806365), Mount Ommaney (0.59,0.691837)

Cases with greater than 0.5 memberships in term ~Damage loss:

Gailes (1,0.665228), North Ipswich (0.999036,0.604998), Barellan (0.982642,0), Graceville (0.981678,0.670622), Redbank (0.980714,0.806365), Yeronga (0.978785,0.779216), Moorooka (0.977821,0.615067), Karalee (0.967213,1), Mount Ommaney (0.945998,0.691837), Paddington (0.934426,1), Woolloongabba (0.906461,0.530924), Sherwood (0.901639,0.726897), Chelmer (0.89296,0.748472), Fairfield (0.875603,0.750629), Yeerongpilly (0.873674,0.951816), Goodna (0.798457,0.0880978), Tennyson (0.766635,0.242898), Kholo (0.685632,0.790004), Greenslopes (0.512054,0.640417)

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 10 months = f (Recovery funds, Economic stability, %Not single family detached houses, ~SoVI, Damage loss, House price change)

Rows: 20

Algorithm: Quine-McCluskey

True: 1

--- INTERMEDIATE SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.894592

Assumptions:

- Recovery funds (present)
- Economic stability (present)
- %Not single family detached houses (present)
- ~SoVI (present)
- ~Damage loss (absent)
- House price change (present)

	Raw Coverage	Unique Coverage	Consistency
Recovery funds*Economic stability*~SoVI	0.55	0.29	0.85
Economic stability*%Not single family detached houses*~SoVI*~Damage loss	0.38	0.13	0.92

Solution coverage: 0.675366

Solution consistency: 0.873540

Cases with greater than 0.5 memberships in term Recovery funds*Economic stability*~SoVI:

Graceville (0.801634,0.670622), Karalee (0.8,1), Kholo (0.77,0.790004), Chelmer (0.766752,0.748472), Tennyson (0.759524,0.242898), Jindalee (0.723308,0.550521), Barellan (0.7,0), Sherwood (0.67,0.726897), Fairfield (0.614852,0.750629), Yeronga (0.613099,0.779216), Mount Ommaney (0.59,0.691837), Oxley (0.561114,0.730313)

Cases with greater than 0.5 memberships in term Economic stability*%Not single family detached houses*~SoVI*~Damage loss:

Tennyson (0.759524, 0.242898), Yeronga (0.613099, 0.779216), Yeerongpilly (0.611059, 0.951816), Sherwood (0.605781, 0.726897), Paddington (0.581752, 1), Fairfield (0.558767, 0.750629), Moorooka (0.539871, 0.615067), Greenslopes (0.512054, 0.640417)

Recovery Outcome 2: Housing reconstruction after 10 months

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 13months = f (House price change, Damage loss, ~SoVI, %Not single family detached houses, Economic stability, Recovery funds)

Rows: 6

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.933719

	Raw Coverage	Unique Coverage	Consistency
House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.33	0.12	0.93
~House price change*Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.20	0.60	0.93
~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability*Recovery funds	0.24	0.08	0.97

Solution coverage: 0.476147

Solution consistency: 0.935582

Cases with greater than 0.5 memberships in term House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds:

Graceville (0.801634, 0.858798), Kholo (0.564754, 0.877253), Mount Ommaney (0.545609, 0.646781)

Cases with greater than 0.5 memberships in term ~House price change*Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds:

Jindalee (0.601452, 0.698712), Oxley (0.561114, 0.75279)

Cases with greater than 0.5 memberships in term ~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability*Recovery funds:

Sherwood (0.605781, 0.586695), Yeronga (0.563348, 0.642489), Fairfield (0.532252, 0.734764), Tennyson (0.514187, 0.606009)

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 13months = f (House price change, Damage loss, ~SoVI, %Not single family detached houses, Economic stability, Recovery funds)

Rows: 6

Algorithm: Quine-McCluskey

True: 1-L

--- PARSIMONIOUS SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.933719

	Raw Coverage	Unique Coverage	Consistency
House price change	0.53	0.22	0.87
Damage loss*Recovery funds	0.25	0.06	0.90
%Not single family detached houses*Recovery funds	0.31	0.07	0.87

Solution coverage: 0.675114

Solution consistency: 0.856224

Cases with greater than 0.5 memberships in term House price change:

Graceville (0.999932, 0.858798), Paddington (0.582696, 1), Corinda (0.568545, 0.191416), Kholo (0.564754, 0.877253), Mount Ommaney (0.545609, 0.646781)

Cases with greater than 0.5 memberships in term Damage loss*Recovery funds:

Jindalee (0.805207, 0.698712), Oxley (0.69, 0.75279), Riverview (0.584378, 1)

Cases with greater than 0.5 memberships in term %Not single family detached houses*Recovery funds:

Yeronga (0.793488, 0.642489), Tennyson (0.781299, 0.606009), Redbank (0.62, 1), Sherwood (0.605781, 0.586695), Fairfield (0.558767, 0.734764)

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 13months = f(Recovery funds, Economic stability, %Not single family detached houses, ~SoVI, Damage loss, House price change)

Rows: 8

Algorithm: Quine-McCluskey

True: 1

--- INTERMEDIATE SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.933719

Assumptions:

- Recovery funds (present)
- Economic stability (present)
- %Not single family detached houses (present)
- ~SoVI (present)
- ~Damage loss (absent)
- House price change (present)

	Raw Coverage	Unique Coverage	Consistency
Recovery funds*Economic stability*%Not single family detached houses*~SoVI	0.27	0.05	0.92
Recovery funds*Economic stability*~SoVI*Damage loss	0.21	0.04	0.93
Recovery funds*Economic stability*~SoVI*House price change	0.39	0.11	0.92

Solution coverage: 0.491912

Solution consistency: 0.918984

Cases with greater than 0.5 memberships in term Recovery funds*Economic stability*%Not single family detached houses*~SoVI:

Tennyson (0.759524, 0.606009), Yeronga (0.613099, 0.642489), Sherwood (0.605781, 0.586695), Fairfield (0.558767, 0.734764)

Cases with greater than 0.5 memberships in term Recovery funds*Economic stability*~SoVI*Damage loss:

Jindalee (0.723308, 0.698712), Oxley (0.561114, 0.75279)

Cases with greater than 0.5 memberships in term Recovery funds*Economic stability*~SoVI*House price change:

Graceville (0.801634, 0.858798), Kholo (0.564754, 0.877253), Mount Ommaney (0.545609, 0.646781)

Recovery Outcome 3: Housing reconstruction after 17 months

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 16 months = f(House price change, Damage loss, ~SoVI, %Not single family detached houses, Economic stability, Recovery funds)

Rows: 6

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.939277

	Raw Coverage	Unique Coverage	Consistency
~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability	0.32	0.17	0.98
House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.30	0.11	0.94
~House price change*Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.19	0.06	0.99

Solution coverage: 0.529060

Solution consistency: 0.951679

Cases with greater than 0.5 memberships in term ~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability:

Yeerongpilly (0.611059, 1), Sherwood (0.605781, 0.851994), Yeronga (0.563348, 1), Moorooka (0.539871, 0.651074), Fairfield (0.532252, 0.904908), Tennyson (0.514187, 0.374233), Greenslopes (0.512054, 0.739264)

Cases with greater than 0.5 memberships in term House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds:

Graceville (0.801634, 0.83589), Kholo (0.564754, 1), Mount Ommaney (0.545609, 0.842025)

Cases with greater than 0.5 memberships in term ~House price change*Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds:

Jindalee (0.601452, 0.596626), Oxley (0.561114, 0.852761)

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 16 months = f (House price change, Damage loss, ~SoVI, %Not single family detached houses, Economic stability, Recovery funds)

Rows: 6

Algorithm: Quine-McCluskey

True: 1-L

--- PARSIMONIOUS SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.939277

	Raw Coverage	Unique Coverage	Consistency
~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability	0.50	0.15	0.92
House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.45	0.16	0.90
~House price change*Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.24	0.05	0.95

Solution coverage: 0.724115

Solution consistency: 0.884368

Cases with greater than 0.5 memberships in term House price change:

Graceville (0.999932, 0.83589), Paddington (0.582696, 1), Corinda (0.568545, 0.444018), Kholo (0.564754, 1), Mount Ommaney (0.545609, 0.842025)

Cases with greater than 0.5 memberships in term %Not single family detached houses:

Greenslopes (1,0.739264), Yeerongpilly (0.928957,1), Woolloongabba (0.793662,0.596626), Yeronga (0.793488,1), Tennyson (0.781299,0.374233), Redbank (0.654884,1), Sherwood (0.605781,0.851994), Moorooka (0.59899,0.651074), Paddington (0.581752,1), Fairfield (0.558767,0.904908)

Cases with greater than 0.5 memberships in term Damage loss*Recovery funds:

Jindalee (0.805207, 0.596626), Oxley (0.69, 0.852761), Riverview (0.584378, 1)

****

TRUTH TABLE ANALYSIS

****

Model: % Reconstructed in 16 months = f (Recovery funds, Economic stability, %Not single family detached houses, ~SoVI, Damage loss, House price change)

Rows: 10

Algorithm: Quine-McCluskey

True: 1

--- INTERMEDIATE SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.939277

- Assumptions:
- Recovery funds (present)
- Economic stability (present)
- %Not single family detached houses (present)
- ~SoVI (present)
- ~Damage loss (absent)
- House price change (present)

	Raw Coverage	Unique Coverage	Consistency
~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability	0.34	0.15	0.94
House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.20	0.03	0.96
~House price change*Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.35	0.10	0.93

Solution coverage: 0.541843

Solution consistency: 0.921182

Cases with greater than 0.5 memberships in term Economic stability*%Not single family detached houses*~SoVI*~Damage loss:

Tennyson (0.759524, 0.374233), Yeronga (0.613099, 1), Yeerongpilly (0.611059, 1), Sherwood (0.605781, 0.851994), Paddington (0.581752, 1), Fairfield (0.558767, 0.904908), Moorooka (0.539871, 0.651074), Greenslopes (0.512054, 0.739264)

Cases with greater than 0.5 memberships in term Recovery funds*Economic stability*~SoVI*Damage loss:

Jindalee (0.723308, 0.596626), Oxley (0.561114, 0.852761)

Cases with greater than 0.5 memberships in term Recovery funds*Economic stability*~SoVI*House price change:

Graceville (0.801634, 0.83589), Kholo (0.564754, 1), Mount Ommaney (0.545609, 0.842025)

Recovery Outcome 4: Housing resilience index

****

TRUTH TABLE ANALYSIS

****

Model: Reconstruction index = f (House price change, Damage loss, ~SoVI, Recovery funds, Economic stability, %Not single family detached houses)

Rows: 6

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.929371

	Raw Coverage	Unique Coverage	Consistency
~House price change*~Damage loss*~SoVI*%Not single family detached houses*Economic stability	0.29	0.24	0.94
House price change*~Damage loss*~SoVI*~%Not single family detached houses*Economic stability*Recovery funds	0.18	0.12	0.97

Solution coverage: 0.414251

Solution consistency: 0.964884

Cases with greater than 0.5 memberships in term ~House price change*~Damage loss*~SoVI*Economic stability*%Not single family detached houses:

Yeerongpilly (0.611059, 0.935275), Sherwood (0.605781, 0.751888), Yeronga (0.563348, 0.498382), Moorooka (0.539871, 0.988134), Fairfield (0.532252, 0.422869), Tennyson (0.514187, 0.892125), Greenslopes (0.512054, 0.998921)

Cases with greater than 0.5 memberships in term ~House price change*Damage loss*~SoVI*~Recovery funds*Economic stability*~%Not single family detached houses:

Jamboree Heights (0.695315, 0.971953), Anstead (0.64, 0.971953), Sinnamon Park (0.551591, 0.979504)

****

TRUTH TABLE ANALYSIS

****

Model: Reconstruction index = f (House price change, Damage loss, ~SoVI, Recovery funds, Economic stability, %Not single family detached houses)

Rows: 6

Algorithm: Quine-McCluskey

True: 1-L

--- PARSIMONIOUS SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.929371

	Raw Coverage	Unique Coverage	Consistency
~Recovery funds	0.55	0.23	0.96
%Not single family detached houses	0.44	0.12	0.92

Solution coverage: 0.666525

Solution consistency: 0.937099

Cases with greater than 0.5 memberships in term ~Recovery funds:

Greenslopes (1,0.998921), Moorooka (1,0.988134), North Ipswich (0.92,0.83603), Jamboree Heights (0.83,0.971953), Woolloongabba (0.83,0.952535), Yeerongpilly (0.83,0.935275), Sinnamon Park (0.77,0.979504), Corinda (0.67,0.824164), Paddington (0.67,0.924488), Anstead (0.64,0.971953)

Cases with greater than 0.5 memberships in term %Not single family detached houses:

Greenslopes (1,0.998921), Yeerongpilly (0.928957,0.935275), Woolloongabba (0.793662,0.952535), Yeronga (0.793488,0.498382), Tennyson (0.781299,0.892125), Redbank (0.654884,0.933118), Sherwood (0.605781,0.751888), Moorooka (0.59899,0.988134), Paddington (0.581752,0.924488), Fairfield (0.558767,0.422869)

****

TRUTH TABLE ANALYSIS

****

Model: Reconstruction index = f(%Not single family detached houses, Economic stability, Recovery funds, ~SoVI, Damage loss, House price change)

Rows: 12

Algorithm: Quine-McCluskey

True: 1

--- INTERMEDIATE SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.929371

Assumptions:

- %Not single family detached houses (present)
- Economic stability (present)
- Recovery funds (present)
- ~SoVI (present)
- ~Damage loss (absent)
- House price change (present)

	Raw Coverage	Unique Coverage	Consistency
Economic stability*~Recovery funds*~SoVI	0.39	0.16	0.98
%Not single family detached houses*Economic stability*~SoVI*~Damage loss	0.32	0.98	0.95

Solution coverage: 0.484047

Solution consistency: 0.956313

Cases with greater than 0.5 memberships in term Economic stability*~Recovery funds*~SoVI:

Sinnamon Park (0.729341, 0.979504), Jamboree Heights (0.695315, 0.971953), Paddington (0.67, 0.924488), Anstead (0.64, 0.971953), Yeerongpilly (0.611059, 0.935275), Greenslopes (0.572201, 0.998921), Corinda (0.562433, 0.824164), Moorooka (0.539871, 0.988134)

Cases with greater than 0.5 memberships in term %Not single family detached houses*Economic stability*~SoVI*~Damage loss:

Tennyson (0.759524, 0.892125), Yeronga (0.613099, 0.498382), Yeerongpilly (0.611059, 0.935275), Sherwood (0.605781, 0.751888), Paddington (0.581752, 0.924488), Fairfield (0.558767, 0.422869), Moorooka (0.539871, 0.988134), Greenslopes (0.512054, 0.998921)

Recovery Outcome 5: Housing resilience index

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 10 months= f (Damage loss, SEIFA, Insurance, ~SoVI, %Not single family detached houses, Not vulnerable population, Recovery funds, Economic stability)

Rows: 5

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.853475

	Raw Coverage	Unique Coverage	Consistency
Damage loss*SEIFA*~Insurance*~SoVI*~%Not single family detached houses*Not vulnerable population*~Recovery funds*Economic stability	0.33	0.33	0.85

Solution coverage: 0.328734

Solution consistency: 0.853475

Cases with greater than 0.5 memberships in term Damage loss*SEIFA*~Insurance*~SoVI*~%Not single family detached houses*Not vulnerable population*~Recovery funds*Economic stability:

Jamboree Heights (0.695315, 0.872708), Anstead (0.64, 0.37073), Sinnamon Park (0.551591, 0.42197), Corinda (0.518544, 0.622438)

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 10 months= f (Damage loss, SEIFA, Insurance, ~SoVI, %Not single family detached houses, Not vulnerable population, Recovery funds, Economic stability)

Rows: 5

Algorithm: Quine-McCluskey

True: 1-L

--- PARSIMONIOUS SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.853475

	Raw Coverage	Unique Coverage	Consistency
Damage loss	0.48	0.48	0.64

Solution coverage: 0.477800

Solution consistency: 0.640454

Cases with greater than 0.5 memberships in term Damage loss:

Jamboree Heights (1, 0.872708), Corinda (0.907425, 0.622438), Jindalee (0.805207, 0.449479), Oxley (0.701061, 0.269687), Anstead (0.650916, 0.37073), Riverview (0.584378, 0), Sinnamon Park (0.551591, 0.42197)

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 10 months= f (Economic stability, Recovery funds, Not vulnerable population, %Not single family detached houses, ~SoVI, Insurance, SEIFA, Damage loss)

Rows: 16

Algorithm: Quine-McCluskey

True: 1

--- INTERMEDIATE SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.853475

Assumptions:

- ~Economic stability (absent)
- ~Recovery funds (absent)
- ~Not vulnerable population (absent)
- ~%Not single family detached houses (absent)
- ~~SoVI (absent)
- ~Insurance (absent)
- ~SEIFA (absent)
- Damage loss (present)

	Raw Coverage	Unique Coverage	Consistency
~Recovery funds*~%Not single family detached houses*~Insurance*Damage loss	0.35	0.35	0.83

Solution coverage: 0.353078

Solution consistency: 0.830824

Cases with greater than 0.5 memberships in term ~Recovery funds*~%Not single family detached houses*~Insurance*Damage loss:

Jamboree Heights (0.83, 0.872708), Anstead (0.64, 0.37073), Sinnamon Park (0.551591, 0.42197), Corinda (0.518544, 0.622438)

Recovery Outcome 6: not recovered after 13 months

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 13 months= f (Damage loss, SEIFA, Insurance, ~SoVI, %Not single family detached houses, Not vulnerable population, Economic stability, Recovery funds)

Rows: 5

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.690867

	Raw Coverage	Unique Coverage	Consistency
Damage loss*SEIFA*~Insurance*~SoVI*~%Not single family detached houses*Not vulnerable population*Economic stability*~Recovery funds	0.32	0.20	0.78
~Damage loss*SEIFA*~Insurance*~SoVI*%Not single family detached houses*Not vulnerable population*Economic stability*~Recovery funds	0.34	0.22	0.69

Solution coverage: 0.542688

Solution consistency: 0.707686

Cases with greater than 0.5 memberships in term Damage loss*SEIFA*~Insurance*~SoVI*~%Not single family detached houses*Not vulnerable population*Economic stability*~Recovery funds:

Jamboree Heights (0.695315, 0.63133), Anstead (0.64, 0.414592), Sinnamon Park (0.551591, 0.367382), Corinda (0.518544, 0.808584)

Cases with greater than 0.5 memberships in term ~Damage loss*SEIFA*~Insurance*~SoVI*%Not single family detached houses*Not vulnerable population*Economic stability*~Recovery funds:

Yeerongpilly (0.611059, 0), Paddington (0.581752, 0), Moorooka (0.539871, 0.812876), Greenslopes (0.512054, 0.438197)

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 13 months= f (Damage loss, SEIFA, Insurance, ~SoVI, %Not single family detached houses, Not vulnerable population, Economic stability, Recovery funds)

Rows: 5

Algorithm: Quine-McCluskey

True: 1-L

--- PARSIMONIOUS SOLUTION ---

Frequency cut-off: 2.000000

Consistency cut-off: 0.690867

	Raw Coverage	Unique Coverage	Consistency
~Recovery funds	0.68	0.68	0.55

Solution coverage: 0.675733

Solution consistency: 0.547770

Cases with greater than 0.5 memberships in term ~Recovery funds:

Greenslopes (1,0.438197), Moorooka (1,0.812876), North Ipswich (0.92,0.265665), Yeerongpilly (0.83,0), Jamboree Heights (0.83,0.63133), Woolloongabba (0.83,0.677682), Sinnamon Park (0.77,0.367382), Corinda (0.67,0.808584), Paddington (0.67,0), Anstead (0.64,0.414592)

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 13 months= f (Recovery funds, Economic stability, Not vulnerable population, %Not single family detached houses, ~SoVI, Insurance, SEIFA, Damage loss)

Rows: 80

Algorithm: Quine-McCluskey

True: 1

--- INTERMEDIATE SOLUTION ---

Frequency cut off: 2.000000

Consistency cut off: 0.690867

Assumptions:

- ~Recovery funds (absent)
- ~Economic stability (absent)
- ~Not vulnerable population (absent)
- ~%Not single family detached houses (absent)
- ~SoVI (absent)
- ~Insurance (absent)
- ~SEIFA (absent)
- Damage loss (present)

	Raw Coverage	Unique Coverage	Consistency
~Recovery funds*~Insurance	0.67	0.67	0.55

Solution coverage: 0.675369

Solution consistency: 0.547960

Cases with greater than 0.5 memberships in term ~Recovery funds*~Insurance:

Greenslopes (1,0.438197), Moorooka (1,0.812876), North Ipswich (0.92,0.265665), Yeerongpilly (0.83,0), Jamboree Heights (0.83,0.63133), Woolloongabba (0.83,0.677682), Sinnamon Park (0.77,0.367382), Corinda (0.666667,0.808584), Paddington (0.666667,0), Anstead (0.64,0.414592)

Recovery Outcome 7: not recovered after 17 months

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 16 months= f (Damage loss, SEIFA, Insurance, ~SoVI, %Not single family detached houses, Not vulnerable population, Recovery funds, Economic stability)

Rows: 5

Algorithm: Quine-McCluskey

True: 1

--- COMPLEX SOLUTION ---

Frequency cut off: 2.000000

Consistency cut off: 0.703494

	Raw Coverage	Unique Coverage	Consistency
Damage loss*SEIFA*~Insurance*~SoVI*~%Not single family detached houses*Not vulnerable population*~Recovery funds*Economic stability	0.37	0.37	0.70

Solution coverage: 0.366816

Solution consistency: 0.703494

Cases with greater than 0.5 memberships in term Damage loss*SEIFA*~Insurance*~SoVI*~%Not single family detached houses*Not vulnerable population*~Recovery funds*Economic stability: Jamboree Heights (0.695315, 0.743098), Anstead (0.64, 0.272239), Sinnamon Park (0.551591, 0.398773), Corinda (0.518544, 0.555982)

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 16 months= f (Damage loss, SEIFA, Insurance, ~SoVI, %Not single family detached houses, Not vulnerable population, Recovery funds, Economic stability)

Rows: 5

Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---

Frequency cut off: 2.000000

Consistency cut off: 0.703494

	Raw Coverage	Unique Coverage	Consistency
Damage loss	0.52	0.37	0.51

Solution coverage: 0.518079

Solution consistency: 0.512983

Cases with greater than 0.5 memberships in term Damage loss:

Jamboree Heights (1, 0.743098), Corinda (0.907425, 0.555982), Jindalee (0.805207, 0.403374), Oxley (0.701061, 0.147239), Anstead (0.650916, 0.272239), Riverview (0.584378, 0), Sinnamon Park (0.551591, 0.398773)

****

TRUTH TABLE ANALYSIS

****

Model: ~%Reconstructed in 16 months= f (Economic stability, Recovery funds, Not vulnerable population, %Not single family detached houses, ~SoVI, Insurance, SEIFA, Damage loss)

Rows: 16

Algorithm: Quine-McCluskey

True: 1

-- INTERMEDIATE SOLUTION ---

Frequency cut off: 2.000000

Consistency cut off: 0.703494

Assumptions:

- ~Economic stability (absent)
- ~Recovery funds (absent)
- ~Not vulnerable population (absent)
- ~%Not single family detached houses (absent)
- ~SoVI (absent)
- ~Insurance (absent)
- ~SEIFA (absent)
- Damage loss (present)

	Raw Coverage	Unique Coverage	Consistency
~Recovery funds*~%Not single family detached houses*~Insurance*Damage loss	0.39	0.39	0.67

Solution coverage: 0.387649

Solution consistency: 0.673817

Cases with greater than 0.5 memberships in term ~Recovery funds*~%Not single family detached houses*~Insurance*Damage loss:

Jamboree Heights (0.83, 0.743098), Anstead (0.64, 0.272239), Sinnamon Park (0.551591, 0.398773), Corinda (0.518544, 0.555982)