SPATIAL ANALYSIS AND MODELLING OF FLOOD RISK AND CLIMATE ADAPTATION CAPACITY FOR ASSESSING URBAN COMMUNITY AND CRITICAL INFRASTRUCTURE INTERDEPENDENCY

A Dissertation submitted by

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For the award of

Doctor of Philosophy

2014

Abstract

Flood hazards are the most common and destructive of all natural hazards in the world. A series of floods that hit the south east region of Queensland in Australia from December 2010 to January 2011 caused a massive devastation to the State, people, and its critical infrastructures. GIS-based risk mapping is considered a vital component in land use planning to reduce the adverse impacts of flooding. However, the integrated mapping of climate adaptation strategies, analysing interdependencies of critical infrastructures, and finding optimum decisions for natural disaster risk reduction in floodplain areas remain some of the challenging tasks. In this study, I examined the vulnerability of an urban community and its critical infrastructures to help alleviate these problem areas. The aim was to investigate the vulnerability and interdependency of urban community's critical infrastructures using an integrated approach of flood risk and climate adaptation capacity assessments in conjunction with newly developed spatially-explicit analytical tools.

As to the research area, I explored Brisbane City and identified the flood-affected critical infrastructures such as electricity, road and rail, sewerage, stormwater, water supply networks, and building properties. I developed a new spatially-explicit analytical approach to analyse the problem in four components: 1) transformation and standardisation of flood risk and climate adaptation capacity indicating variables using a) high resolution digital elevation modelling and urban morphological characterisation with 3D analysis, b) spatial analysis with fuzzy logic, c) geospatial autocorrelation, among others; 2) fuzzy gamma weighted overlay and topological cluster analyses using Bayesian joint conditional probability theory and self-organising neural network (SONN); 3) examination of critical infrastructure interdependency using utility network theory; and 4) analysis of optimum natural disaster risk reduction policies with Markov Decision Processes (MDP).

The flood risk metrics and climate adaptation capacity metrics revealed a geographically inverse relationship (e.g. areas with very high flood risk index occupy a low climate adaptation capacity index). Interestingly, majority of the study area (93%) exhibited negative climate adaptation capacity metrics (-22.84 to < 0) which indicate that the resources (e.g. socio-economic) are not sufficient to increase the climate resiliency of the urban community and its critical infrastructures. I utilised these sets of information in the vulnerability assessment of critical infrastructures at single system level. The January 2011 flood instigated service disruptions on the following infrastructures: 1) electricity supplies along 627km (75%) and 212km (25%) transmission lines in two separate areas; 2) road and rail services along 170km (47%) and 2.5km (38%) networks, respectively; 3) potable water supply along 246km (56%) distribution lines; and 4) stormwater and sewerage services along 33km (91%) and 32km (78%) networks, respectively.

From the critical infrastructure interdependency analysis, the failure of sewerage system due to the failure of electricity supply during the January 2011 flood exemplified the first order interdependency of critical infrastructures. The ripple effects of electricity failure down to road inaccessibility for emergency evacuation demonstrated the higher order interdependency. Moreover, an inverted pyramid

structure demonstrated that the hierarchy of climate adaptation strategies of the infrastructures was graded from long-term measures (e.g. elimination) down to short-term measures (e.g. protection).

The analysis with Markov Decision Processes (MDP) elucidated that the Australian Commonwealth government utilised the natural disaster risk reduction expenditure to focus on recovery while the State government focused on mitigation. There was a clear indication that the results of the MDP analysis for the State government established an agreement with the previous economic analysis (i.e. mitigation could reduce the cost of recovery by 50% by 2050 with benefit-cost ratio of 1.25).

The newly developed spatially-explicit analytical technique, formulated in this thesis as the *flood risk-adaptation capacity index-adaptation strategies (FRACIAS) linkage model*, integrates the flood risk and climate adaptation capacity assessments for floodplain areas. Exacerbated by the absence of critical infrastructure interdependency assessment in various geographic analyses, this study enhanced the usual compartmentalised methods of assessing the flood risk and climate adaptation capacity of flood plain areas. Using the different drivers and factors that exposed an urban community and critical interdependent infrastructures to extreme climatic event, this work developed GIS-enabled systematic analysis which established the nexus between the descriptive and prescriptive modelling to climate risk assessment.

Certification of Dissertation

I certify that the ideas, experimental work, results, analyses, software and conclusions reported in this dissertation are entirely my own efforts, except where otherwise acknowledged. I also certify that the work is original and has not been previously submitted for any other award, except where otherwise acknowledged.

Signature of Candidate	Date

ENDORSEMENT

Signature of Principal Supervisor	Date

Signature of Associate Supervisor	Date

Publications and Awards

Peer-Reviewed Conference Papers

Chapter 3

Espada, R., Apan, A. & McDougall, K., 2012. *Spatial modelling of adaptation strategies for urban built infrastructures exposed to flood hazards. In: Queensland Surveying and Spatial Conference 2012 (QSSC 2012), 13-14 Sept 2012*. Brisbane City, Surveying and Spatial Sciences Institute.

Espada, R. J., Apan, A. & McDougall, K., 2013. *Understanding the January 2011 Queensland flood: the role of geographic interdependency in flood risk assessment for urban community. In: Australia and New Zealand Disaster and Emergency Management Conference (ANZDMC) 2013, 28-30 May 2013*. Brisbane City, AST Management Pty Ltd. pp. 68-88. ISBN: 978-1-922232-04-5.

Chapters 4 to 5

Espada, R., Apan, A. & McDougall, K., 2013. *Using spatial modelling to develop flood risk and climate adaptation capacity metrics for vulnerability assessments of urban community and critical water supply infrastructure. In: 49th International Society of City and Regional Planners (ISOCARP) Congress 2013, 1-4 October 2013*. Brisbane City, International Society of City and Regional Planners (ISOCARP). ISBN: 978-94-90354-25-1.

Espada, R., Apan, A. & McDougall, K., 2013. *Using spatial modelling to develop flood risk and climate adaptation capacity metrics for assessing the vulnerability of urban community and critical electricity infrastructure. In: 20th International Congress on Modelling and Simulation (MODSIM) 2013,* Adelaide, Modelling and Simulation Society of Australia and New Zealand (MSSANZ), pp. 2304-2310. ISBN: 978-0-9872143-3-1.

Journal Papers

Chapter 5

Espada, R., Apan, A., McDougall, K, 2014. Vulnerability Assessment and Interdependency Analysis of Critical Infrastructures for Climate Adaptation and Resiliency. Manuscript submitted on 28 February 2014 to *International Journal of Disaster Resilience in the Built Environment* for publication.

Chapter 6

Espada, R., Apan, A., McDougall, K, 2014. Spatial Modelling of Natural Disaster Risk Reduction Policies with Markov Decision Processes. Manuscript accepted on 20 June 2014 in *Applied Geography* for publication.

Awards

2013 ESRI Young Scholar Award for Australia – ESRI Australia and ESRI USA

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2013 ACSC Postgraduate Student Seminar Research Paper Presentation First Prize Winner – International Centre for Applied Climate Sciences, University of Southern Queensland

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2011 Endeavour Postgraduate Award (Australia Awards) – Australian Government Department of Education

Acknowledgments

Foremost, I would like to express my sincere appreciation to my Principal Supervisor, Associate Professor Armando Apan for his wisdom, direction and motivation all throughout this research journey. The guidance of my Associate Supervisor, Professor Kevin McDougall, significantly helped me in framing up this thesis right from the very beginning. Access and funding support for the spatial datasets used in this study were also made possible because of their genuine generosity.

Besides my supervisors, my sincere gratitude goes to the Australian Government through the Department of Education for the Endeavour Postgraduate Award and the team from Austraining International for providing the financial support and scholarship management support, respectively.

This thesis would neither be accomplished nor completed without the access to other spatial datasets. As such, my heartfelt appreciations go as well to the Australian Bureau of Statistics (ABS), Brisbane City Council (BCC), Energex Ltd., Queensland Fire and Rescue Service (QFRS), Queensland Department of Environment and Resource Management (DERM), and Queensland Government Information Service (QGIS).

Finally, deepest thanks to my family, Marilou and Patricia Zelene, who have been very patient and understanding for my “absence” during the final stages of this thesis.

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Abbreviations

3D	Three-Dimensional
ABS	Australian Bureau of Statistics
AC	Adaptation Capacity
AEP	Average Exceedance Probability
AER	Australian Energy Regulator
ANN	Artificial Neural Network
ARI	Annual Recurrence Interval
AOV	Assigned Ordinal Value
BCC	Brisbane City Council
BCR	Benefit-Cost Ratio
BOM	Bureau of Meteorology
BTRE	Bureau of Transport and Resources Economics
CA	Climate Adaptation
CCA	Climate Change Adaptation
CEC	Commission of the European Communities
CCIQ	Chamber of Commerce and Industries Queensland
CIS	Critical Infrastructure System
CO	Cluster and Outlier
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DBM	Digital Building Model
DCCEE	Department of Climate Change and Energy Efficiency
DCS	Department Community Safety
DEFRA	Department for Environment, Food and Rural Affairs
DEM	Digital Elevation Model
DERM	Department of Environment and Resource Management
DEWS	Department of Energy and Water Supply
DNRM	Department of Natural Resources and Mines
DOTARS	Department of Transport and Regional Services
DRR	Disaster Risk Reduction
DSM	Digital Surface Model
DTM	Digital Terrain Model
DTMR	Department of Transport and Main Roads
EHP	Environment and Heritage Protection
EMQ	Emergency Management Queensland

ENSO	El Niño/Southern Oscillation
EPA	Environmental Protection Agency
ERT	Emergency Response Time
FMV	Fuzzy Membership Values
FR	Flood Risk
FRACIAS	Flood Risk - Adaptation Capacity Index - Adaptation Strategies
FSE	Fuzzy Synthetic Evaluation
FSI	Floor Space Index
GIS	Geographic Information System
H	High Risk (Rating of flood risk model)
HH	High Values Surrounded by High Values
HL	High Values Surrounded by Low Values
IAG	Insurance Australia Group
ICC	Ipswich City Council
IDW	Inverse Distance Weight
IEO	Index for Education and Occupation
IER	Index for Economic Resources
IPCC	Intergovernmental Panel on Climate Change
IRSAD	Index of Relative Socio-Economic Advantage and Disadvantage
IRSD	Index of Relative Socio-Economic Disadvantage
KML	Keyhole Markup Language
L	Low Risk (Rating of flood risk model)
LH	Low Values Surrounded by High Values
LiDAR	Light Detection and Ranging
LL	Low Values Surrounded by Low Values
M	Moderate Risk (Rating of flood risk model)
MDP	Markov Decision Processes
NDRRA	Natural Disaster Relief and Recovery Arrangements
NFRAG	National Flood Risk Advisory Group
NS	Not Significant
PFR	Perceived Flood Risk Level
QCA	Queensland Competition Authority
QCM	Quadrat Counting Method
QFCI	Queensland Floods Commission of Inquiry
QFRS	Queensland Fire and Rescue Service
QGIS	Queensland Government Information Service
QRA	Queensland Reconstruction Authority

QUDM	Queensland Urban Drainage Manual
QUU	Queensland Urban Utilities
RDA	Rapid Damage Assessment
SEIFA	Socio-Economic Index for Areas
SEQ	South East Queensland
SOM	Self-Organising Map
SONN	Self-Organising Neural Network
SoQ	State of Queensland
TC	Tropical Cyclones
TIFF	Tagged Image File Format
UNDP	United Nations Development Programme
UNISDR	United Nations International Strategy for Disaster Reduction
UQ-CGQ	University of Queensland Centre for Government Queensland
VH	Very High Risk (Rating of flood risk model)

Chapter 1

INTRODUCTION

1.1 Background

Flood hazards are the most common and destructive of all natural hazards (Vanneuville *et al*. 2011) and flood damages had been estimated to be the most costly in Australia (BTRE 2002 and Geoscience Australia 2010a). To reduce the impact of flooding, flood hazard mapping has been considered a vital component for appropriate land use planning in flood prone areas (Linham and Nicholls 2010). In doing so, flood forecasts are usually determined by examining past occurrences of flooding events, determining recurrence intervals of historical events (known as Annual Recurrence Interval), and then extrapolating to future probabilities (known as Average Exceedance Probability) (Baer 2008). Taking along with forecasts, nowcasting can also be done by describing in details the current weather through extrapolation of weather data (e.g. radar echoes) for a period of 0 to 6 hours ahead (WMO n.d.).

The estimation of the Average Exceedance Probability (AEP) of extreme floods is grouped into two broad categories: the statistical streamflow modelling methods and rainfall-runoff modelling methods (Smith *et al.* 2010). These modelling and mapping techniques produce a better understanding of the causes and magnitude of disastrous flooding. Furthermore, these methods will provide flood information necessary to support the development of an integrated strategy to improve disaster resilience and preparedness in the flood hazard reduction areas (Teasdale *et al.* 2010).

With the widespread use of Geographic Information System (GIS) and database resources, models and inundation maps can be easily updated and improved, significant flood information can be generated, and potential hazards or risks associated with locating critical infrastructures can be determined (Teasdale *et al.* 2010). Despite GIS increasingly becoming more analytical (Berry 1995), an integrated approach in mapping climate adaptation strategies for flood risk management remains a challenging task. Engineering profession must respond to these challenges by working in new ways using the integrated systems approach (Collins *et al*. 2011). This approach requires a framework which can address adaptation challenges of a system (e.g. urban infrastructure system) exposed to variable and changing climate in an integrated and systematic manner. In a built environment, strong interdependency of infrastructures exists. This interdependency sets the interaction of the different forms of infrastructures to provide various social services. For example, the energy infrastructure (e.g. electricity) keeps the business and industries, communication, medical, educational, and other social services operational. The failure to supply energy will consequently disrupt the entire system. Traditionally, climate adaptation action for infrastructures has tended to be individualised or compartmentalised among the different camps of water, electricity, transportation, residential houses, commercial and industrial buildings, education, and public health and safety, etc. The policy, research and implementing agencies treated them separately – an approach analogous to a “pigeon-hole”. Hence, the research gap on spatial modelling and vulnerability assessment of integrated critical infrastructures as significant research contribution in providing policies for flood risk management and climate adaptation strategies was examined.

1.2 Research Problems and Significance

The impacts of climate on our ecological and socio-economic systems will most likely affect several sectors like food, industry, settlement and society, health, and water (Parry *et al.* 2007). In the urban setting, for example, some cities will face difficulties in providing basic services to their inhabitants like energy and water supply, physical infrastructure, transportation, ecosystem goods and services, and industrial production (UN Habitat 2011). Furthermore, the United Nations estimates that by 2025, half of the world’s population will be living in areas that are at risk from storms and other weather extremes (Heller *et al.* 2003). Thus, there is an urgent need to develop natural disaster risk reduction measures and climate adaptation strategies to help minimise the harmful effects of extreme weather events like floods.

In Australia, the Government has funded a number of projects under the Climate Change Adaptation Program to improve knowledge of the impacts of climate change, strengthen the capacity of decision-makers to respond and address major areas of national vulnerability (DCCEE 2010). The current recommended strategies are to manage climate risk through mitigation (i.e. net reductions in greenhouse gas emissions) and adaptation to unavoidable climate impacts (CSIRO 2007). In support to the latter strategy, this study examined the vulnerability of an urban community and its critical infrastructures exposed to extreme flood event.

In New York City, the New York City Climate Change Adaptation Task Force (NYC CCATF) evaluated the vulnerability of its infrastructures to climate change with emphasis on coastal flooding and developed adaptation strategies such as maintenance and operations (e.g. temporary flood gates, cleaning of drainage systems, etc.), capital investments (e.g. installation of new flood barriers, elevating elements of critical infrastructure to levels above projected flood elevations), and regulatory (e.g. modification of city building codes and design standards (McLaughlin *et al.* 2011). In The Netherlands, the urban water managers in the city of Rotterdam developed a new water management strategy through a transformative water management approach by combining urban design with a climate adaptation strategy (Graaf and Brugge 2010). In New Zealand, a study was conducted to understand the impact of climate changes on the interconnected infrastructure systems and services (ISS) in Hamilton City (Jollands *et al.* 2006).

Whilst these studies offer a magnitude of lessons, each has its own drawbacks. The asset-specific adaptation strategies for critical infrastructures identified in the New York City could be addressed by the integrated approach in the Hamilton City study. However, the latter lacked the transformative approach through a multi-level perspective which has been thoroughly discussed in the Rotterdam study.

Conversely, the Rotterdam study lacks an emphasis on the importance of infrastructure interdependencies as thoroughly presented in the Hamilton City study. Infrastructure interdependency refers to the networks of infrastructures wherein the operation of individual infrastructure sector relies on other sectors, e.g. energy, water and transport networks depend on information and communication technology (ICT) infrastructure for control and monitoring of their conditions, which entails dependency on energy (Collins *et al.* 2011). Thus, infrastructure interdependencies are highly critical considering that extreme events are responsible to 'cascade failure' where the failure of one aspect of infrastructure can lead to complete fragmentation of interdependent networks (Buldyrev *et al.* 2010).

In identifying natural disaster risk reduction policies and climate adaptation strategies, the Geographic Information System (GIS) and remote sensing technologies play a significant role in climate impact assessment process. Their capability to handle and analyse thematic maps with high accuracy, time- and cost-efficiency has been demonstrated in various disciplines. With its wide range of applications and modelling functions, these technologies are popular tools in disaster risk management. Thus, the successful utilisation of these technologies in disaster management is crucial (Altan *et al.* 2010) for study of historical events (Islam and Sado 2000), a major tool in planning (Ernst and Mostafa 2010), and to map spatial distribution of flood risk and vulnerability (Karmakar *et al*. 2010). As a tool, GIS can be used for analysing climate impacts, identifying the risks and opportunities that will need to be responded to, defining the geographical areas most sensitive to climate change, and identifying appropriate adaptation responses (Liu 2009).

A GIS-based framework can provide a scientific understanding of earth systems and leads to more thoughtful and informed decision making (Dangermond and Baker 2010) to combat the potential harmful effects of extreme climatic conditions. However, the greatest priority is to develop responses or strategic actions that can work within the high uncertainty of future climate change, to build resilience, and maintain flexibility (Hunt and Watkiss 2010). In prioritising strategic responses for climate adaptation and natural disaster risk reduction, decision-makers are confronted with competing financial resources. Hence, in an increasingly competitive financial environment, government expenditures for disaster risk reduction should be spent optimally without losing the efficacy of finest delivery of infrastructure services to communities.

Having identified the significant issues mentioned above, this study was challenged to fill in the following research gaps and thereby produced significant academic and practical contributions to this area of research:

1. The universal way of representing and analysing flood risk through maps is descriptive (e.g. low, moderate, high, and very high risk). This study, however, extends beyond the descriptive model of representing flood risk and climate adaptation capacity indices to include the prescriptive model of representing climate adaptation policies and strategies for flood risk management under extreme climatic condition. Prescriptive modelling refers to the characterisation of direct and indirect factors related to system response used in determining appropriate management action (Berry

1995). This research area has never been substantially explored in flood risk assessment studies.

The linkage between descriptive and prescriptive modelling techniques is presented in Chapters 3, 4 and 6.

2. The pigeon-hole approach has been the common method of analysing infrastructure exposure to flood hazards which separately analyses risk for different types of infrastructure (e.g. water, electricity, sewerage, etc.). An infrastructure asset is said to be *critical* if its disruption would cause social inconvenience. This study introduced an integrated approach of analysing infrastructure risk to damage due to flooding (in general) and identifying critical interdependent infrastructure assets (in particular) that are exposed and vulnerable to flood hazards. Infrastructure interdependency refers to the networks of infrastructures wherein the performance of one relies on the other (Collins *et al.* 2011). The critical infrastructures analysed in this study were electricity, water supply, sewerage, stormwater, roads and rails, and building properties. They were selected based on the availability of spatial information. Chapter 5 identifies the ways and discusses the means of addressing the issue.

3. Finally, the spatial modelling to find optimal decisions for disaster risk reduction by setting the problem as Markov decision process was also examined in this study – an approach that has not been comprehensively studied to support the natural disaster risk reduction efforts. This is also fully discussed in Chapter 6.

1.3 Research Objectives

The aim of this study was to investigate the vulnerability and interdependency of urban community's critical infrastructures using an integrated approach of flood risk and climate adaptation capacity assessment in conjunction with newly developed spatially-explicit analytical tools.

Specifically, the objectives of this study were the following:

1. To develop a comprehensive set of flood risk and climate adaptation capacity metrics as inputs for modelling natural disaster risk reduction and climate adaptation strategies;
2. To assess the vulnerability of an urban community and its critical interdependent infrastructures exposed to flood hazard for the development of integrated climate adaptation strategies; and
3. To examine the optimality of natural disaster risk reduction policies being implemented in an urban community and its critical infrastructures.

In achieving these objectives, this study hypothesised that: "*Spatially explicit flood risk and climate adaptation capacity models can provide sets of information that are useful in planning and developing adaptation strategies from the potential effects of extreme flood event to the physical assets (human settlement and critical infrastructure systems) of an urban community.*"

1.4 Location of the Study Area

The study area is located in the core suburbs of Brisbane City, the Queensland's capital in Australia (see Figure 1.1). The City is traversed by the 345-kilometer long Brisbane River, which is the longest river in South East Queensland and flows down from Mount Stanley to Moreton Bay (Middelman 2002). Including the Lockyer Creek and Bremer River catchments, around 6,500 km^2 (approximately 50%) of the Brisbane River catchment is below Wivenhoe and Somerset Dams (Robinson 2011). Completed in 1984, the Wivenhoe Dam was built as a dual-purpose storage for both drinking water (which supplies water to the City) and flood mitigation (SEQ Water 2012).

Described as Australia's New World City with strong economic growth, Brisbane City had an $85 billion economy in 2011, almost half of the State economy (BCC 2011). However, the Brisbane's economic progress together with more than a million estimated residents, had been hampered and devastated recently by 2010/2011 floods. In January 2011, the Brisbane River broke its banks and inundated the city (Queensland Museum 2011). Flood waters in Brisbane peaked at 4.46 metres making it one of the worst floods since the January 1974 flood when Brisbane River reached 5.45 metres (BOM 2013). The flood caused significant damage on the City's infrastructures, assets, transport, waterways, and community areas with an estimated damage bill in excess of $440 million (BCC 2012b).

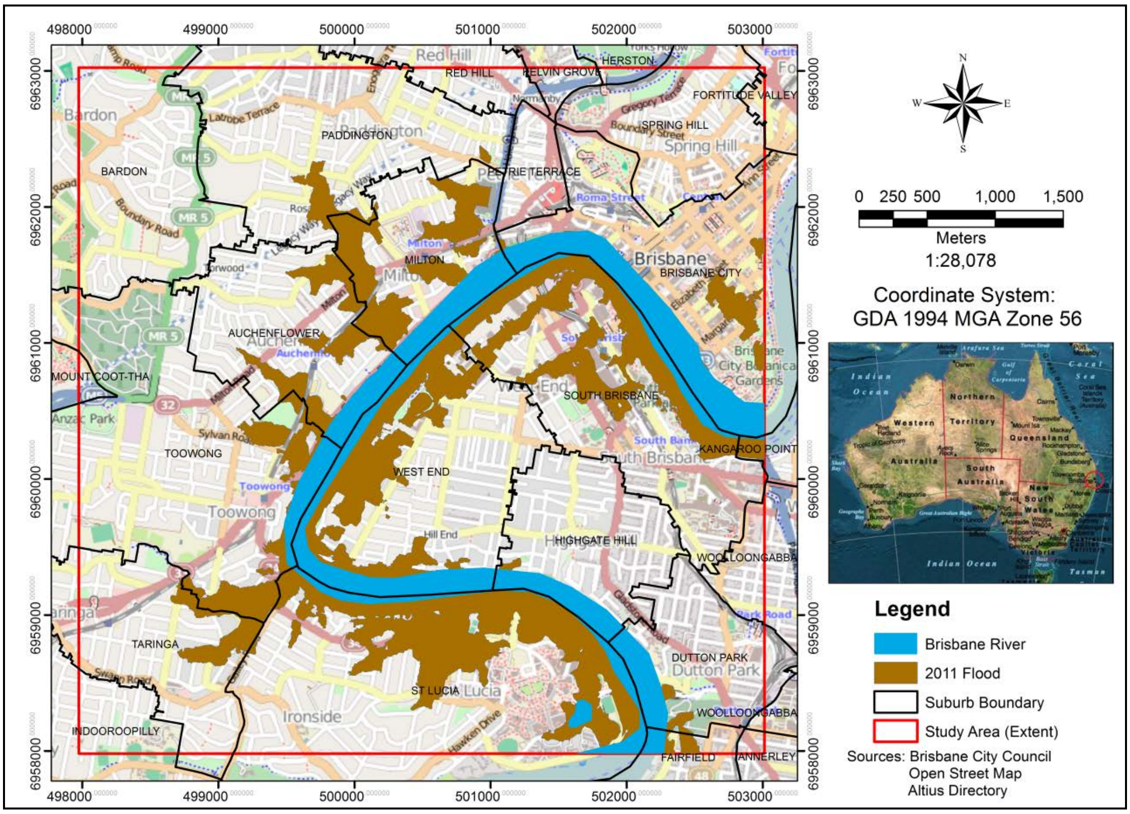


Figure 1.1 The location map of the study area

Comprising an area of approximately 2,200 ha, the study area includes the 22 suburbs of the City: South Brisbane, West End, Highgate Hill, Brisbane Central Business District (CBD), Toowong, Auchenflower, and portions of Spring Hill, Paddington, Bardon, St. Lucia, and Dutton Park, etc.. The extent of this study area was chosen based on available high resolution LiDAR dataset.

On the South Brisbane side, the study area is home to major cultural attractions and art galleries, Australia's only beach in a city, Brisbane's best restaurants and cafes, and one of the East Queensland's most popular tourist destinations. Aside from offering tourism services to an estimated 10 million people each year, the area is devoted to several land uses such as recreation parks, commerce and business, industry, education, residential, cultural centres and museum, State Library of Queensland, among others (South Bank Corporation 2012). Within the CBD, the centre takes the role of the Queensland's principal vicinity for business and administration complemented by retailing, entertainment, education, community and cultural facilities, tourism and residences (BCC 2010).

1.5 Overview of Research Methods

This study developed an integrated approach of formulating climate adaptation strategies to reduce vulnerability of an urban community and infrastructure assets from floods and the long-term effects of extreme climatic events. Figure 1.2 is the input-process-output (IPO) model specifically used in this study. Highlighted in the figure were data inputs used, processes involved, and the outputs generated from the comprehensive analysis. Under the input component, the flood hazard, vulnerability, and exposure indicators were assessed (also see Table 3.1). Under the process component, four (4) main GIS operation challenges were addressed to generate the flood risk and adaptation capacity metrics. The first challenge was to identify analytical tools with ArcGIS 10 (ESRI 2011) that will transform indicating variables (i.e. indicators that describe observable variables) for flood hazard, vulnerability, and exposure into standardised raster formats. The digital elevation modelling and urban morphological characterisation with 3D analysis, spatial analysis with fuzzy logic, proximity, quadrat, collect events analyses, hot spot and line statistical analyses were primarily operationalised. Each of this preliminary analytical technique was used according to the type of geographic feature being represented by the indicating variable (Table 3.1).

This study was also challenged to apply the spatial autocorrelation techniques with emphasis on Global Moran's I and Cluster and Outlier Analysis of Anselin Local Moran's I. These techniques were applied to measure the dispersion of urban development, critical infrastructures, emergency services, and flood-related hazards that suggest a measure of perceived level of flood risk in an urban community. The application and conceptualisation of these techniques are a challenging task considering that direct interpolation techniques of point data, for example, renders inaccurate results in clustering highly vulnerable infrastructures. The initial outputs generated from the spatial autocorrelation analyses were then summarised in raster using the Inverse Distance Weight (IDW) method of point data interpolation. The generated raster maps were then carefully analysed to assign categorised values for each indicating variable that generally explain perceived level of flood risk.
The second challenge was to evaluate which of these variables have certain degree of direct correlation (pattern similarity) with perceived flood risk and which of them can be potentially included in the weighted overlay analysis. The issue was resolved

by creating transformation algorithm of the raster maps in MATLAB version R2011b program (The Mathworks, Inc. 2013) and analysed the topological clusters of these indicating variables using the self-organising neural network (SONN) mapping tool. Selection was then made as to which of the indicating variables were included in the weighted overlay operations.

The third challenge was to address the limitations of deductive and normative arguments in climate risk assessment. As such, varying degrees of importance (unequal weights) of indicating variables were generated using Bayesian probability. These probability values were used in the weighted overlay operations in generating consequential hazard, physical vulnerability, and exposure indices. These indices were in turn used in calculating the flood risk metrics using the modified fuzzy gamma function. Applying Equations 3.1 to 3.6, the flood risk and climate adaptation capacity metrics were generated.
The final outputs (i.e. flood risk and adaptation capacity metrics) were then applied in assessing the vulnerability of urban community and critical infrastructures. Finally, optimal decision modelling was performed to assess the optimum natural disaster risk reduction policies implemented by the Commonwealth government of Australia and, the State government of Queensland.

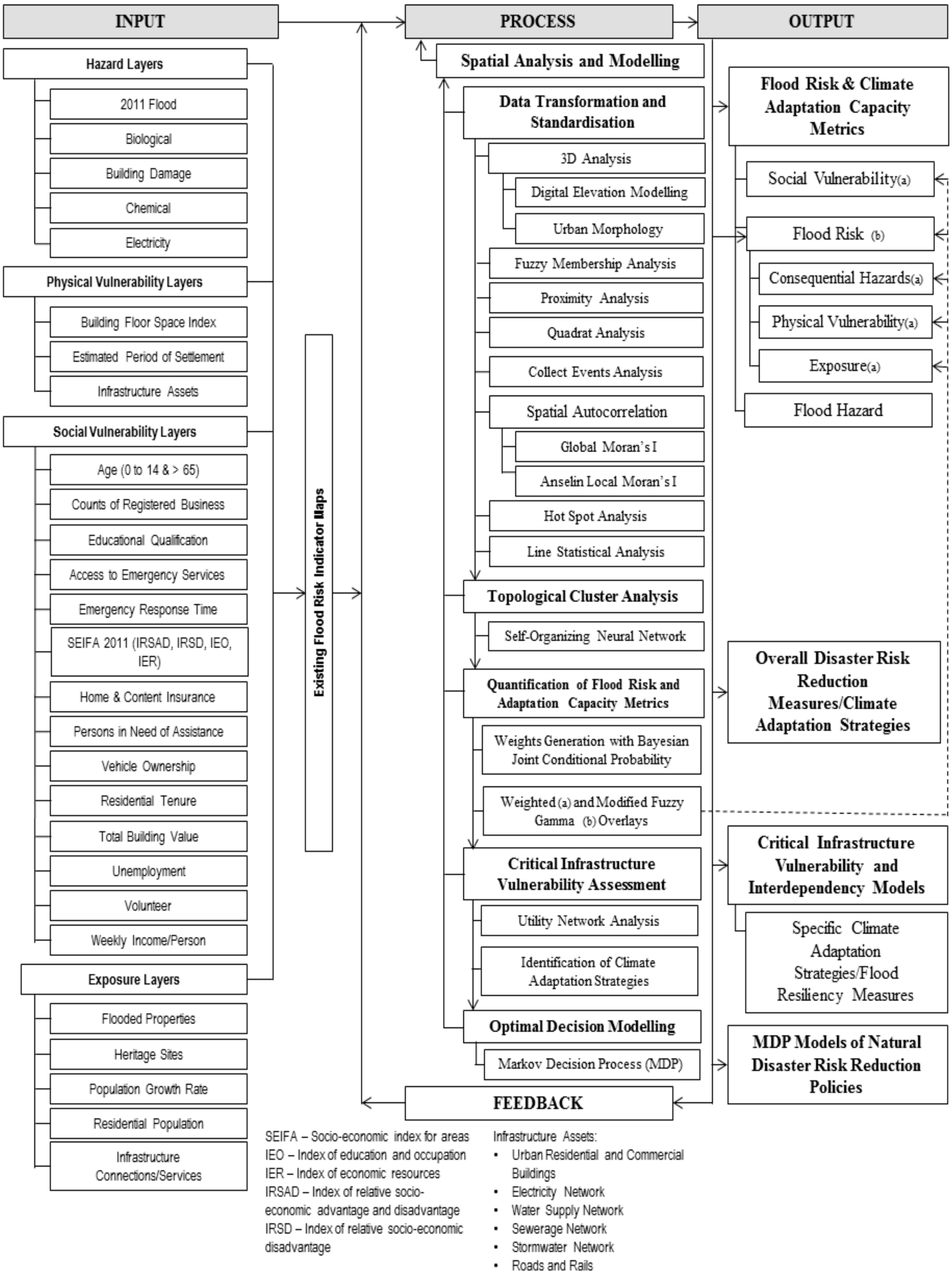


Figure 1.2 The input-process-ouput (IPO) model used in the study

1.6 Scope and Limitation of the Study

The study was scoped based on several considerations: availability of spatial datasets, single flood event (i.e. January 2011 flood), and strategic locations of significantly flooded critical interdependent infrastructures in an urban community (i.e. Brisbane City). The rationale and key considerations in the way how this study was scoped were based on the recommendations of Queensland Floods Commission of Inquiry to look at solutions to limit the consequences of infrastructure failure from severe weather events like the January 2011 flood in Brisbane. As a very topical and significant issue, the Commission was established by the State government of Queensland to investigate into what had happened during the December 2010-January 2011 floods in south east region of the state and provide recommendatory actions to increase Queensland's resiliency from flooding. The information from this inquiry based on actual flood events gave this study an opportunity to bring GIS and remote sensing as tools to help find the solutions.

A variety of limitations can be identified in this study. The most obvious one is the extent of the study area. Its selection was approached on the basis of availability of high resolution LiDAR data. Ideally, flood risk assessment should be done through the ecosystem approach either on the basis of flood plain or catchment area. However, none of this approach was considered due to the absence of a wider LiDAR coverage to scope the entire flood plain or catchment area.

The second limitation is the absence of temporal analysis of flood risk. Due to unavailability of data which relate to historical extreme flood events, this study opted to settle on a single flood event data particularly the actual extent of the January 2011 flood. Furthermore, due to complexity and unfeasibility to "predict" the future conditions of Brisbane City and its critical interdependent infrastructures in the future, the climate change factors for assessing future flood risk in the study area were also excluded in the analysis. Hence, the absence of temporal dynamics of flood risk is acknowledged in this study.

To fully assess the vulnerability of the study area and its critical infrastructures, ICT infrastructure, broadband, gas storage and distribution, ports and airports, food supply, waste, financial, and other networked infrastructures were desired to be included in the analysis. However, the availability and the confidentiality of some datasets hindered to include them in the analysis.

Furthermore, the effect of integrating hydrologic and hydraulic analysis in the flood risk assessment has also been disregarded in this study. Instead of using them as tools in flood risk assessment, it was assumed that the actual flood extent could provide better and accurate modelling information.

Finally, the assumptions associated with the variables in setting the Markov decision processes (MDP) were mainly based on existing literature; hence, no actual experimentation was performed.

1.7 Organisation of the Thesis

This thesis is organised into seven chapters with schematic representation shown in Figure 1.3.

The *First Chapter* presents the introductory background to the research, poses the research problems and significance, and sets out the objectives.

The *Second Chapter* reviews the areas of knowledge that are relevant to this study: geographic information system (GIS) and natural disaster risk assessment. The use of spatial layers in flood risk and climate adaptation capacity assessments is discussed along with critical infrastructure interdependency modelling and optimising disaster risk reduction policies. In a nutshell, this Chapter provides the nexus amongst the flood risk, climate adaptation capacity, critical infrastructure interdependency, and disaster risk reduction policies of the examined urban community.

Chapter 3 describes the spatial analytical tools that were utilised to transform and standardise flood risk and climate adaptation capacity indicating variables. This Chapter serves as the “gateway” to Chapters 4, 5 and 6.

Chapter 4 covers the development of flood risk and climate adaptation capacity metrics through the applications of Self-Organising Neural Network (SONN), Bayesian joint conditional probability, weighted overlay, and fuzzy gamma overlay techniques in GIS.

The *Fifth Chapter* covers the methods of assessing the vulnerability of critical infrastructures along with interdependency analysis. The specific and integrated climate adaptation strategies to increase climate resiliency of the study area and its critical infrastructures are also discussed.

Chapter 6 applies the optimisation technique called Markov Decision Processes (MDP) to find natural disaster risk reduction policies funded by the Australian governments. Lastly, the *Final Chapter* covers the conclusions and recommendations for future works.

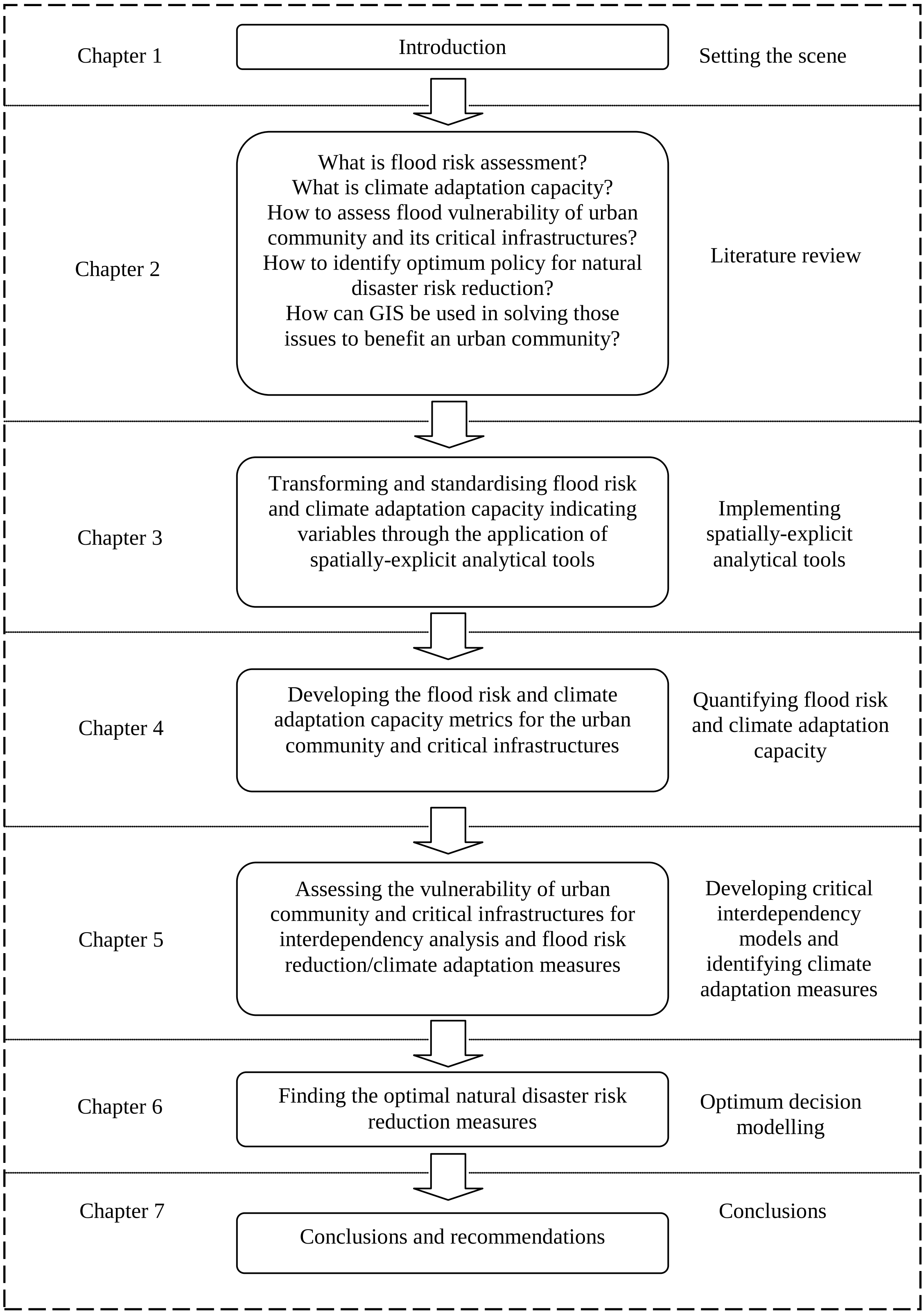


Figure 1.3 The schematic layout of the Thesis

Chapter 2

LITERATURE REVIEW

The first Chapter presented the overall framework on the potential use of GIS and remote sensing in the natural disaster risk management. This second Chapter is a review on the relationships of various factors affecting the flood risk and climate adaptation capacity assessments of urban community and critical infrastructures. Furthermore, this Chapter establishes the niche for disaster risk reduction and climate adaptation, as well as the relevant sciences and technologies of GIS and remote sensing. In summary, Chapter 2 provides the journey towards exploring the relationship of the three major components of this study: (1) flood risk-climate adaptation capacity assessments; (2) vulnerability assessment of critical infrastructures and their interdependencies; and (3) identification and analysis of natural disaster risk reduction measures.

2.1 Overview of the Climate System

As a complex system, the Earth's climate is controlled primarily by the exchange and storage of heat through the atmosphere, ocean, and biosphere (Dai *et al.* 2001; Whitfield *et al.* 2010). Once any of the components are changed, it may give rise to change in the climatic conditions on different scales of time and in different ways (Bradley 2015). For example, the equatorial location of the tropical rainforest and high sun angles all throughout the year make the tropical region high in terms of annual temperatures with very little seasonal variation (Ritter 2006). In the late 1970s, the atmospheric science community had begun reporting on the potential for a warming of the global climate as a result of increased gaseous pollutants released into the atmosphere (Changnon 1995).

Whilst others are having an ongoing political debate on climate change (Heinke *et al.* 2013) due to the absence of much evidence (Tol 2013), others argue that there is evidence to suggest that climate change may have already affected ecosystem services and human society (Gosling 2013). Over the past 25 years, temperatures have increased at a rate of 0.19^0C per decade, in very good agreement based on greenhouse gas predictions with the trend continues to be one of warming (Allison *et al.* 2009). High temperatures cause more extreme climatic events by putting heat-trapping gases into the atmosphere (Wagner and Zeckhauser 2011). The global increase in the number of hurricanes of the strongest categories 4 and 5 and intense tropical activities have been associated by the rising sea surface temperatures (SST) as the leading cause (Allison *et al.* 2009).

2.2 Climate and Climate Change in Australia and Queensland

As a large island continent in the southern hemisphere, Australia has a diverse range of climate zones characterised by the following (BOM 2011):

- The northern part, interior, and southern part of the continent has tropical, arid, and temperate climatic conditions, respectively;
- The country is a relatively arid country with 80% of the land receiving 600 mm annual rainfall and 50% receiving less than 300 mm.
- The south eastern coastal cities are characterised as wetter zone – where most Australians are living.

A country that is very vulnerable to the effects of climate change, Australia's climatic conditions had been altered significantly. Since 1910, the average temperature of the country has risen by 1°C and estimated to face the following by 2030 (DCCEE 2011):

- a further 1°C of warming in temperatures;
- up to 20 % increase in drought;
- up to 25 % increase in the days of very high or extreme fire danger; and
- increase in storm surges and severe weather events.

In Queensland, the climatic conditions across the area are considerably varied as summarised in the following Table (BOM 2011).

Table 2.1 The Queensland's climatic conditions

Geographic Location	Climatic Condition
Inland west	Low rainfall and hot summers
North	Monsoon season
Coastal strip	Warm temperate
Southern ranges	Low minimum temperatures

The warm waters of the Coral and Tasman Seas influence the climate of the coastal strip with an annual median rainfall ranging from 1000 to 6000 mm increasing to over 3200 mm along parts of the northern coast (BOM 2011). In coastal regions, tropical cyclones (from November to May) are a natural hazard (BOM 2011).

In a report released by the Queensland's Office of Climate Change in 2008, the following key findings were emphasised (Whitfield *et al.* 2010):

- Year 2000-2009 was the hottest on record with temperatures 0.58^{o}C higher than the 1961-1990 average;
- Queensland regions can expect increased temperatures of between 1.0^{o}C and 2.2^{o}C by 2050;
- Rainfall is expected to change, with a potential decrease by up to seven per cent (7%) in central Queensland by 2050;
- A three to five per cent (3-5%) decrease in rainfall in the south-east Queensland region is projected; and
- Sea levels are rising faster than expected.

As a result of climate change, Queensland is likely to experience impacts like increased flooding, erosion and damage in coastal areas due to increased numbers of severe tropical cyclones and sea level rise (Whitfield *et al.* 2010).

Australia has historically been impacted by various flood disasters and recently the December 2010 to January 2011 floods in south east Queensland. Floods are estimated to be the most costly natural disaster in Australia (Geoscience Australia 2011). The average direct annual cost of flooding between 1967 and 1999 has been estimated at $314 million. The most costly flood was recorded in 1974 amounting to $2.9 billion (Geoscience Australia 2010); which has been, however, superseded by the 2010/2011 Queensland floods.

2.3 Floods in Queensland and other Australian States

Were the December 2010 to January 2011 floods in south east Queensland caused by anthropogenic climate change?

In an interview of ABC Radio National with Stewart Franks, a hydrologist from the University of Newcastle, the latter described that extreme climatic events in Eastern Australia were associated with El Niño and La Niña events (Franks 2011). These events tended to cluster into what referred as the multi-decadal epochs of climate variability such that during these periods, El Niño may be dominant bringing droughts between 20 to 40 year periods and subsequently replaced by La Niña events for another 20 to 40 year periods leading to a marked increase in flood risk (Franks 2011). Furthermore, the warm El Niño events are associated with below average rainfall and higher than average temperatures and evaporation, whereas the cool La Niña events typically deliver enhanced rainfall totals and cooler than normal conditions demonstrated that year-to-year flood (and drought) risk varies significantly and that this variability was closely related to El Niño/Southern Oscillation (ENSO) (Kiem *et al.* 2006).

In another view, however, opposite scientists argue that although the global atmospheric warming of about 0.75^{o}C over the past century had some impact, there is no strong reason at the moment to say that La Niña is stronger or worse than it would even without humans (Birsel 2011). Whether the 2010/2011 floods in Queensland and other floods in Australia were caused by climate change or ENSO phenomenon, these were the significant things that are certain - that the flood hazards considerably affected and shaped the economy and history of Australia in general and Queensland in particular as summarised in Table 2.2.

Table 2.2 Flood events in Queensland and other Australian States from 1899 to 2011

Year	Flood Event Description
1899	On 04 March 1899, a category 5 cyclone, named Cyclone Mahina, was one of the Australia's recorded worst natural disasters. Winds reached 260 kilometres per hour that caused tsunami of 14.6 metres. The cyclone swept the inland of Queensland for 5 kilometres. Four hundred (400) people lost their lives. Some sharks and dolphins were left hanging from trees and cliffs (State Library of Queensland 2010).
1918	During the early 1918 (January), Mackay Cyclone was the first two cyclones that inflicted heavy damage on significant population centres in northern Queensland. Thirty (30) people lost their lives mainly from Mackay and Rockhampton due to devastating winds, and storm surge. The phenomenal amount of rainfall (1,411 mm) that lasted for three days generated the worst flood in Mackay's history (ABS 2008).
1929	Twenty two (22) people died from heavy flood when a torrential rainfall, measuring up to 500 mm, hit the Burnie and Ulverstone areas on 03 April 1929. The Briseis Dam on the Cascade River was crumpled, tons of trees, rocks and gravel were carried by heavy

Year	Flood Event Description
	rains, and over 1,000 houses in Launceston were inundated (ABS 2008).
1955	Moving south from Queensland, a monsoon depression deposited the 250-mm rainfall in 24 hours in the Hunter, Macquarie, Namoi and Gwydir River Valleys. The floods lost 14 lives and 15,000 people were evacuated. The flood disaster completely submerged houses and damaged various infrastructure assets like bridges, roads, railways and telephone lines (ABS 2008).
1974	The year 1974 brought devastations in the areas of Brisbane and Darwin. In January, Brisbane was got flooded due to heavy rain from Cyclone Wanda. The 580-mm rainfall in Brisbane and 1,300-mm rainfall at Mt. Glorious made the rivers rose at the highest levels, washed away many houses, and unfortunately killed 14 people (ABS 2008). In December of the same year, Cyclone Tracy brought devastating floods in Darwin. Most buildings were totally destroyed and badly damaged due to extremely fierce winds. Sixty five (65) people died and the remaining population was evacuated. It was then that building codes and aspects of disaster planning were given much attention (ABS 2008).
1975	Since 1910, 48 cyclones have caused gale-force winds at Port Hedland. On the average, a cyclone visited the area once for every two years usually from mid-December to April peaking in February. Cyclone Joan in 1975 had the strongest wind gust recorded at Port Hedland measuring 208 km/h (ABS 2008).
1999	The strong and slow moving upper level trough undercut by cool south-easterly winds caused persistent heavy rainfall in the Esperance region for few days. This climatic event made the area significantly flooded. Rainfall record reached 209 mm - the heaviest rainfall event since rainfall records began in 1899 (ABS 2008).
2006	Carrying gale-force winds of up to 290 km/h, category 5 Cyclone Larry smashed into the far-north Queensland coast. The cyclone significantly uprooted trees, lifted roofs of houses and flattened crops on the 20th of March 2006. The estimated loss of infrastructure and crops between the areas of Babinda and Tully was at $500M. Larry caused a significant storm surge with inundation record as high as 4.9 metres above the expected at Bingil Bay. Mulgrave, Tully, Murray Rivers and Gulf Rivers were similarly flooded caused by rainfall associated with cyclone (ABS 2008).
2007	Between the 8th and 11th of June 2007, the regions of Hunter and Central Coast of New South Wales were lashed with torrential downpours and gale-force winds. Flash floods urged thousands of residents to abandon their homes. Consequently, a section of Old Pacific Highway collapsed and electric powers were cut. The three-day wild storms lost nine (9) lives on the record. In July 2007, Victoria's Gippsland was under the state's worst flood in a decade. Homes, businesses and farms were significantly lost amounting to millions of dollars. The rising flood waters caused by 48-hour torrential rains urged the residents for rescue and evacuation (ABS 2008).
2010-2011	From December 2010 to January 2011, a series of floods hit Australia, particularly in the state of Queensland, with three quarters of the state declared a disaster zone with over 2.5 million people affected (QRA 2011). Areas like Brisbane City, Rockhampton, Emerald, Bundaberg, Dalby, Toowoomba and Ipswich were devastated by floods. During the early hours of Christmas Day of 2010, a category 1 Tropical Cyclone Tasha brought significant rain in the broad area of northern Queensland. Thirty-five (35) people died, 29,000 homes and businesses suffered from inundation, and flood damaged the region with an estimated amount of over $5 billion (QFCI 2011). Between 2nd and 3rd of February 2011, Category 5 Tropical Cyclone Yasi once again devastated the state of Queensland. The areas of Innisfail and Townsville were the destructive core of the cyclone. Tully and Cardwell suffered major damage to structures and vegetation. The 24-hour total rainfall measured 200-300 mm caused flooding in some areas of Cairns and Ayr. The highest total were recorded in Mission Beach (471 mm), Hawkins Creek (464 mm), Zattas (407 mm), and Bulgun Creek (373 mm). A 5-metre tidal surge was observed at Cardwell, which is 2.3 metre above the Highest Astronomical Tide (HAT) (BOM 2011).

2.4 Flood Risk Assessment

A potentially damaging phenomenon (i.e. flood hazard) is considered a disaster when it brings damage, loss or destruction to the socio-economic system of populated areas (Westen2002). A methodology that is meant to determine the nature and extent of risk by analysing the potential hazards and evaluating the conditions of vulnerability and potential it may cause to people, property, services, livelihoods and the environment is termed as *risk assessment* (UNISDR (2009). In various risk assessment studies, protection of people and assets has been the primordial concern.

2.4.1 Risk components and its relationship

The highly recognised expression of risk is represented by Crichton's (1999) three-dimensional pyramid which comprises of three elements: hazard, vulnerability, and exposure. If any of these elements increases or decreases, the risk increases or decreases, respectively; hence, the greater the contribution of one of the factors, the greater the risk there would be (Dwyer *et al.* 2004) as shown in the following Figure. As the colour of the pyramid gets from being red to green, the risk level decreases.

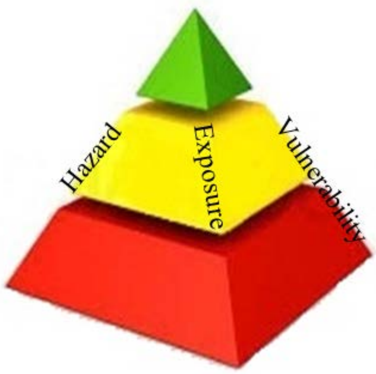


Figure 2.3 The Crichton's (1999) risk triangle/pyramid after Dwyer *et al.* (2004)

Fundamental in understanding the risk assessment process is to understand what is meant by the term *risk.* Risk is defined as the combination of the probability of an event and its negative consequences (UNISDR 2009). Whilst engineers tend toward quantitative expressions of risk such as cumulative frequency plots; a corporate risk manager defined the term as a pertinent event for which there is a textual description (Koller 2007). Thus, in this research, risk is proposed to be perceived as a social construct and contextual notion (Jonkman 2007) taking into consideration who contextualises the notion, when and where it has been contextualised, how and for what purpose it has been contextualised.

Two parameters are associated then with risk: 1) probability of occurrence of an event; and 2) impact or consequence (Koller 2007 and UNISDR 2009). Now, the ambiguity arises as to whether it is probability of occurrence of hazard called *event risk*, or the probability of a particular outcome known as *outcome risk* (Brooks 2003). The former refers to the risk of occurrence of any particular hazard or extreme event while the latter refers to the risk of a particular outcome and integrates both the social or inherent vulnerability and the chance of the occurrence of an event that jointly results in losses (Brooks 2003).

Risk can either be classified as (Mirfenderesk and Corkill 2009):

1. *Existing risk* that applies to existing buildings and development on flood-prone area and refers to the risk a community is exposed to as a result of its location on the floodplain;
2. *Future risk* refers to the risk a community may be exposed to either as a result of new development on the floodplain or change in environmental forces as a result of climate change; and
3. *Residual risk* refers to the risk remaining after mitigation. UNISDR (2009) similarly refers this risk that remains in unmanaged form, even when effective disaster risk reduction measures are in place, and for which emergency response and recovery capacities must be maintained.

In the absence of sufficient and reliable data on future and residual risks in relation to the flooding events within the study area, this study mainly focused on existing or current flood risk.

The number of assets (e.g. people, property, systems and other elements) present in hazard zones that are subject to potential losses is termed as *exposure* (UNISDR 2009). In a broader sense, assets are understood to include productive assets (e.g. human, natural, physical, and financial assets); social and political assets (e.g. voting rights, community participation, etc.); and geographical assets (e.g. location of household, population centres, markets, etc.) (Heltberg *et al*. 2008).

Equally important in understanding the concept of asset is how people weigh its significance, such that an asset is said to be *critical* if its disruption would cause social inconvenience. These include primary physical structures, technical facilities and systems which are socially, economically or operationally essential to the functioning of a society or community, both in routine circumstances and in the extreme circumstances of an emergency (UNISDR (2009). For the purpose of this study, *infrastructure assets* refer to the interrelated built, institutional and environmental systems and services (Jollands *et al.* 2006) of an urban community.

When a dangerous phenomenon, substance, human activity or condition potentially damages property or causes loss of life, injury or other health impacts, or environmental damage (UNISDR 2009), that danger brings the system into a *hazard* condition. Phenomena like droughts, floods, storms, episodes of heavy rainfall, and any other physical manifestations of climatic variability or change are some examples of climatic-related hazard (Brooks 2003). In harmonising UNISDR's (2009) and Brooks' (2003) interpretations, it seems apparent that both are intended to mean hazards as either physical or social manifestations of a phenomenon that may cause an undesirable outcome.

In response to the hazard-centric perception of disasters in the 1970s, the term *vulnerability* had been introduced to describe the extent to which people suffer from calamities and their socio-economic circumstances to withstand them (Schneiderbauer and Ehrlich 2004). Learning from these insights, vulnerability then can be perceived as a hazard-centred interpretation such that it has been defined as potential impact of hazard on a system within which the latter's capacity to cope or resist and adversely responded to events in a particular geographic area is defined by its socio-economic resources. The system here may refer to a biophysical system, social system, or a subsystem of a system such as infrastructure system within an urban ecosystem, or the human-environment interactions and social-ecological system.

Interestingly, Geoscience Australia (2010) conceptualised vulnerability as the impact a hazard has on the people, infrastructure, and the economy. When we characterise a vulnerable human being as: 1) capable of being physically, emotionally or spiritually wounded; 2) open to attack or damage (physical, emotional, or spiritual); and 3) lack in defence or support mechanisms (at the levels of government; community; household; and individual) (Schneiderbauer and Ehrlich 2004), then the term vulnerability is analogous to any individual or social grouping that is determined by their capacity to respond to a hazard, rather than by what may or may not happen in the future (Kelly and Adger 2000).

A variety of research in this area espoused a risk-based approach (Merz *et al.* 2010, Aronica *et al.* 2012) to identify spatial patterns of flood risk associated with hazard, vulnerability, and exposure (Kazmierczak and Cavan 2011). Researchers approached their methods and constructs to their analyses in different ways (Boholm 1998) and yet flood risk experts and decision makers still face the challenge of finding techniques and measures to effectively cope with flood hazards (Kellens *et al.* 2013).

The concepts associated with flood risk assessment were useful in this study particularly on the choice of indicating variables, parameters, and risk classification. For example, the term hazard was associated to the January 2011 flood that caused danger to the study area and its consequential hazards such as biological, chemical, building damage, and electricity hazards. Thus, the concept of hazard was considered in this study being not solely and directly attributed to the flood phenomenon but also its consequences that aggravated the danger.

Furthermore, social vulnerability was referred in this study as the political and socio-economic circumstances (e.g. index of education and occupation, insurance, number of emergency volunteers, etc.) that allowed the urban community to withstand the hazards. Sets of information such as building size, height, settlement growth, and number of critical infrastructure assets were also relevant in determining the physical vulnerability (Deichman 2011) and exposure of the study area.

Finally, in the absence of sufficient and reliable data on future and residual risks in relation to the flooding events within the study area, this study mainly focused on the existing or current flood risk type of classification.

2.5 Climate Adaptation Capacity

The way how the terms capacity and adaptation had been conceptualised appears to be similarly multi-dimensional. *Capacity* is defined as the combination of all the strengths, attributes and resources available within a community, society or organisation that can be used to achieve agreed goals (UNISDR 2009). Using these available skills and resources of people to face and manage adverse conditions, emergencies or disasters, the people and the community and organisational systems involved in the process are said to be in the state of *coping capacity* (Bell 2010). Thus, the term capacity is a generic and collective definition while coping capacity encompasses individual, people, community and organisational capacity that require continuing awareness, resources, good management during crises or adverse conditions that would contribute to the reduction of disaster risks (UNISDR 2009).

Within the context of climate science, *adaptation* is defined as any adjustment in ecological, social, or economic systems in response to actual or expected climatic stimuli, and their effects or impacts (IPCC 2001). This term refers to changes in processes or structures - anticipatory and reactive, autonomous and planned, or public and private (Gallopin 2006), to moderate or offset potential damages or to take advantages of opportunities associated with changes in climate (Bosello *et al*. 2009). However, the use of the term *adjustments* poses an issue such that it has been considered antagonistic to the goal of adaptation per se considering that vulnerability of the system remains (Preston and Stafford-Smith 2009). Hence, the term *adaptive capacity* should be viewed as a system response to perturbations or stress factors that are sufficient to make fundamental changes in the system itself, shifting the system to a new state or how the system responds (Gallopin 2006; Preston and Stafford-Smith 2009); hence, may also be referred to as *response capacity* (Tompkins and Adger 2005; Preston and Stafford-Smith 2009).

The terms climate adaptation and disaster risk reduction come into play within this body of knowledge when both are considered short-term and long-term processes. The former requires a long-term vision and strategy on the side of national and local policy makers while the latter has been considered as an approach that greatly contributes to adaptation to a changing climate (UNISDR and EUR-OPA 2011). As such, disaster risk reduction may no longer consider short-term system's response, but has been viewed both as a short-term and long-term strategy focusing on reducing vulnerability to natural hazards by increasing human, social and environmental capacity and improving physical infrastructure to address the projected changes of future climate (UNISDR and EUR-OPA 2011).

Climate change presents a double challenge today whereby the reduction of greenhouse gases through mitigation is necessarily be complemented with adaptation to the impacts of climate change (CEC 2007 and Bosello *et al.* 2009). In the coastal cities of Rotterdam, New York, and Jakarta, Aerts *et al.* (2011) identified flood risk problems and climate adaptation solutions such as updating facilities and use of new building materials; however, they argued that coastal cities focused primarily on flood defences and less on climate adaptation. Mathew *et al.* (2012) tackled a new framework by incorporating the non-economic dimensions (e.g. local knowledge) as potential adaptation options. In a participatory assessment of adaptation strategies to flood risk in Upper Brahmaputra and Danube river basins, Ceccato *et al.* (2011) emphasised the potential use of NetSyMod as a decision support systems (DSS) tool in the field of climate change adaptation and integrated water resources management (IWRM).

In 2009, Maantay and Maroko (2009) examined the potential utility of a mapping method, the Cadastral-based Expert Dasymetric System (CEDS), in estimating the population of New York City at risk from floods. They emphasised that underestimating more vulnerable populations impairs preparedness and relief efforts.

Furthermore, the disjuncture between the local government and the community rendered governance and climate adaptability weak (Fatti and Patel 2013). In Chia, Colombia, Melgarejo and Lakes (2014) developed and applied an integrated assessment of public infrastructure serving as temporary shelter in case of extreme weather events. Using the Collective-Centre Suitability Index, they found that the assessment method offers a flexible screening tool for transitional shelter and local adaptation planning.

In exploring the use of risk assessment approach for climate change adaptation, Suroso *et al.* (2013) mainstreamed several adaptation options such as canalisation and retention pond for lowland areas; detention basin and dam construction for midland areas; and reforestation for high land areas into South Sumatra's development plans. Lawrence *et al.* (2013) explored alternative climate change scenarios for flood frequency analysis and found that the method of evaluation supports a wider range of flood response options that better reflect the changing nature of risk. Lung *et al.* (2013), on the other hand, developed a spatially-explicit regional adaptive capacity index from heat stress, river flood risk and forest fire risk and found that the assessment can serve as a basis for climate adaptation and regional development in Europe.

In understanding the socio-economic consequences and the costs and benefits of climate change adaptation in the European Union, Rojas *et al.* (2013) established a finding that adaptation associated with the increase in protection could be highly cost-effective; however, at the country level, there is a need to consider climate uncertainty in formulating practical adaptation strategies. Zhou *et al.* (2012) adopted an integrated approach by incorporating climate change impact assessment, flood inundation modelling, economic tool, and risk assessment; thereby, they developed a step-by-step process for cost-benefit assessment of climate change adaptation measures. In another study, Wilby and Keenan (2012) distinguished the enabling environment for adaptation (e.g. flood forecasting, contingency planning, institutional reform, insurance and legal incentives, etc.) and implementing measures to manage flood risk (e.g. climate safety factors for new build, upgrading climate resiliency of existing infrastructure, development control, etc.). Finally, Chan *et al.* (2013) developed a generic sustainable flood risk appraisal (SFRA) framework that can be used in flood risk management. They found that the framework can address social, environmental and economic concerns of climate change.

Based on the comprehensive review of recent literature, Wilby *et al.* (2008) emphasised that the emerging policy agenda is heavily focused on building adaptive capacity through improved quantification of uncertainty in extreme events and by identifying areas at greatest risk of future flooding. This finding clearly emphasised that the research gaps identified in this study are of two folds: 1) Although a variety of GIS-enabled frameworks exists that incorporate flood risk and climate adaptation capacity for assessing flood-prone areas, the analysis of urban communities' critical infrastructure interdependency remains isolated; and 2) Cost-effectiveness and economic benefits associated with climate adaption are highly regarded in the literature; however, finding the optimality of natural disaster risk reduction measures and climate adaptation policies needs to be addressed. With the current trend of continuing urbanisation combined with projected future climate changes that will intensify the problems of flooding (Evans *et al.* 2006 and Pitt 2008), a decision support tool for prioritising climate change adaptation (Fitzimons *et al.* 2010) and adaptation responses are urgently needed (Kazmierczak and Cavan 2011).

Finally, the term climate adaptation capacity was examined in this study to provide the sets of information on the urban community's measure of response to extreme climatic events such as flood. This was further exemplified by the social vulnerability of the study area as presented in Chapter 3.2.

2.6 Developing Flood Risk and Climate Adaptation Capacity Indicating Variables

Quantifying flood risk and climate adaptation capacity requires indicators. In a dynamic and complex process of flood risk and climate adaptation capacity assessments, measuring indicators should meet the following criteria: meaningful, understandable, quantifiable, and unambiguous (De Bruijn 2005). An *indicator* can be described as a function from observable variables (Gallopin 1997); and called *indicating variables* to theoretical variables (Hinkel 2011). A *scalar indicator* is one kind of indicator which maps observable variable to one theoretical variable (Hinkel 2011). For instance, the extent of flooded area (observable variable) is used to indicate high level of flood risk (theoretical variable). This kind of inference follows a linear and monotonously increasing or decreasing operation (Hinkel 2011) such that it is illogical and misleading to indicate flooded areas of both having very low and very high flood risk. This thesis follows this rule of argumentation.

There are two ways of developing indicators: the indicator-based approach and simulation-model-based approach (Hinkel 2011). The former is simple and excludes time as an argument whilst the latter is complex and time-dependent (Hinkel 2011). Using the indicator-based approach in this study, the flood risk components that were defined to be indicated include the physical and social vulnerabilities and exposure of an urban community to flood hazard.

The analysis of flood risk indicators is a crucial prerequisite in developing the integrated framework for the flood risk and climate adaptation capacity assessments. Several attempts have been made by various researchers to find indicating variables such as hazard and vulnerability indicators (Wang *et al.* 2011), social vulnerability indicators (Vari *et al.* 2013), and exposure, susceptibility and resilience (Balica *et al.* 2012). Despite flood risk assessment indicators hold great importance, however, they are often neglected (Scheuer 2013). This study highlighted the development of flood risk and climate adaptation capacity indicators using a set of spatial analytical tools and high resolution dataset (i.e. LiDAR point data).

Even with the presence of highly sophisticated mathematical tools and computing machines nowadays, an interesting question in regard to the selection of indicators for inclusion in the flood risk assessment exercise remains a challenging task. In an exceptional flood risk factor analysis conducted by Elmoustafa (2012), a box plot test was used to exclude extremely high parameter that may lead to unrealistic risk factor. The main innovation of this study, however, was the application of artificial intelligence tool identified as self-organising neural network (SONN) in helping address this research issue. A separate section in this Chapter is provided to discuss SONN.

2.6.1 Geographic Information System

As a popular tool in climate and earth system studies, geographic information system (GIS) has the capability to capture and combine flood and climate risk components. Taking into consideration that climate and geography are bilaterally affecting one another, GIS is the single most powerful integrating tool in conducting inventory, analysis, and in the management of extremely complex problem of climate (Artz and Dangermond 2011).

As climatological phenomena are naturally spatially variables, geoinformatics offers a practical solution in managing vast spatial data sets (Joshi *et al.* 2011). Thus, the main purpose of the geospatial tools is to provide information on the earth surface and document the impacts of natural and anthropogenic events on the going changes (Joshi *et al*. 2011). Spatial information then is especially important for monitoring present and future climate as it offers a great potential in handling climate models in both spatial and temporal dimensions (Paudyal *et al.* 2011).

Several studies on flood susceptibility mapping using remote sensing and GIS technologies (Pradhan 2011) were combined with the applications of logistic regression modelling, fuzzy logic, and artificial neural network (McLaughlin *et al.* 2011). However, spatial-based adaptation capacity index and corresponding adaptation policy options have never been substantially studied for critical infrastructure interdependency of an urban community.

2.6.2 Spatial Analytical Techniques

A set of analytical tools was utilised in this study to initially structure the intensity levels of flood risk and climate adaptation capacity of the study area. The choice of these analytical tools was derived from the special characteristics of datasets included in the analysis as fully discussed in the subsequent sections.

2.6.2.1 Three Dimensional (3D) Analysis using Light Detection and Ranging (LiDAR) Data

Urban three-dimensional (3D) model is an increasing demand for various applications such as city planning, microclimate investigation, virtual city reality, etc. (Zhou *et al.* 2004). As an active research domain, 3D analysis allows to measure the terrain elevation, landscape relief and slope, building heights, water depths, tree volumes, etc. for applications stated earlier. This study initially used 3D analysis in digital elevation modelling and urban morphological characterisation for flood risk assessment.

Digital Elevation Modelling (DEM) for Flood Hazard Analysis

One of the important aspects of flood risk assessment deals with a high quality representation of floodplain's terrain and elevation. The creation of 3D databases of terrain and elevation in city areas is an issue of high significance to various applications in cartographic modelling and simulation (Gabet *et al.* 1997). Urban areas, however, are generally difficult to simulate because of the presence of small-scale system features such as roads and buildings (Haile and Rientjes 2005). The use of airborne remote sensing data such as those coming from "Light Detection and Ranging" (LiDAR) allowed this study to produce high resolution data such as digital elevation model (DEM) as input in flood hazard simulation.

Airborne LiDAR data for topographic analysis has been available since the 1980s and this technology has been widely used in a broad range of research and applications such as geomorphology, coastal zone monitoring, forest management, and infrastructural and environmental projects (Werbrouck *et al.* 2011). LiDAR is an active remote sensing technique (Mutlu *et al.* 2008, Werbrouck *et al.* 2011) that uses laser technology to reflect pulses of light from an aerial sensor to the ground surface (Lillesand *et al.* 2004, Alexander *et al.* 2009). To measure the terrain elevation, the laser pulse is used with registered x-, y- and z-coordinates through the laser altimetry (Lloyd and Atkinson 2005, Drosos and Farmakis 2006, Liu 2008, Werbrouck *et al.* 2011).

Several advantages and disadvantages can be associated with the use of airborne LiDAR data. Aside from being expensive and consists of voluminous data (Axelsson 1999, Challis *et al.* 2008, Liu 2008, Werbrouck *et al.* 2011), the interpretability of raw data is limited due to absence of object information (Axelsson 1999, Werbrouck 2011). On the other hand, the main advantage of using airborne LiDAR data is the exceptional planimetric accuracy of centimetre level which allows the production of high resolution Digital Elevation Model (DEM) (Lohr 1998, Axelsson 1999, Drosos and Farmakis 2006, Liu 2008, Werbrouck *et al.* 2011).

Digital Building Modelling (DBM) for Urban Morphological Characterisation

Traditionally, photogrammetry is an important tool in acquiring 3D data and become widely used in generating digital surface model (DSM) or digital terrain model (DTM) due to the efficiency and cost effectiveness of the production process (Zhou *et al.* 2004). In urban landscape modelling, photogrammetry provides objects and landcover of an urban area in three dimensions (3D) (Dowman 2000) through the process of object extraction. The task involves the detection of object of interest and extraction of geometric boundary from remotely sensed data (Sohn and Dowman 2007). The performance of photogrammetric processes, however, degrades mainly because of failures of image matching particularly in dense urban areas using large scale imagery (Zhou *et al.* 2004). The LiDAR remote sensing technology offers a breakthrough in urban environment mapping (Yu *et al.* 2010) and extraordinary capability in gathering highly accurate and densely sampled surface elevation measurements in urban areas allowing accurate delineation of building footprints (Ma 2005, Yu *et al.* 2009, Zhang *et al.* 2006, Yu *et al.* 2010) and generation of buildings in 3D shapes (Gamba and Housmand 2002, Rottensteiner 2003, Forlani *et al.* 2006, Yu *et al.* 2010).

Urban morphological or form characterisation is part of an urban fabrics analysis that gives the basis to understand urban dynamics and consequently to inform urban design and planning (Hamaina *et al.* 2012). A large number of urban morphological variables exist in literatures such as topography, altitude, city size, etc. Edussuriya *et al.* (2011) identified thirty (30) variables and discussed their importance such as in the air quality study in dense residential environments.

In a tsunami risk study conducted by Eckert *et al.* (2012), the physical vulnerability of the study area was determined by using the elevation, building type, and number of floors. In the north-west portion of the study area, it was found very vulnerable to a tsunami impact mainly because, aside from being close to shoreline and located at low elevation, some buildings were not very high and in poor condition (Eckert *et al.* 2012). Hence, building FSI is a significant building density parameter not only in urban planning and design (Edussuriya *et al.* 2011) but also in flood risk assessment. Santo *et al.* (2012) discoursed that, aside from geological and geomorphological factors, urbanisation coupled with the development of tourism increased the risk of an island to landslides and flash floods as evidenced by the presence of high flood water marks on building walls.

The specific use of LiDAR data in building FSI modelling and visualisation was given attention in this study. Literatures cited that the main problems in creating a 3D urban model from LiDAR data are the detection of building edges and in the interpolation of heights (Alexander *et al.* 2009). A variety of methods had been explored to approximate building boundaries by (1) using LiDAR data (Altharty and Bethel 2002, Cho *et al.* 2004), (2) by digitising from aerial photographs (Palmer and Shan 2002), or (3) by using building footprint (Alexander 2009).

2.6.2.2 Spatial Analysis with Fuzzy Logic

Introduced by Zadeh in 1965, fuzzy set theory embraces the membership function to operate over the range of real numbers (0, 1), reflecting the degree of certainty of membership (Brule 1985, Pradhan 2011) instead of using crisp sets that only allow values of 0 or 1 (Jun *et al.* 2013). In GIS-based natural hazard mapping, the idea of using fuzzy logic is to consider the spatial objects on a map (e.g. areas on an evidence map) as members of a set (e.g. areas hazardous to landslide) wherein the unconstrained (subjective judgment) fuzzy membership values must lie in the range 0 and 1 rather than being measured over discrete intervals (Pradhan 2011). As a tool to handle complex problems such as flood risk assessment, fuzzy logic is attractive because it is straightforward to understand and implement, allows flexibility of combining maps, can be readily implemented with GIS language (Pradhan 2011), and manipulates spatial objects of different measurement units into standardised values (Espada *et al.* 2012).

Fuzzy logic has been used for different purposes such as landslide mapping, flood risk assessments by considering climate change impacts, flood disaster validation, and decision-support for environmental impact assessment, among others (Jiang *et al.* 2009, Liu and Lai 2009, Aksoy and Ercanoglu 2012, Jun *et al.* 2013). In the past decades, increasing interest among researchers and scientists focused on the synergy between GIS and fuzzy logic to analyse Earth observation data.

Flood risk management is always associated with some degree of uncertainty: (1) uncertainty caused by inherent hydrologic variability such as spatial and temporal and uncertainty due to a lack of knowledge; (2) uncertainty in quantification of social values and flood impacts that imparts subjectivity in the decision-making process; and (3) uncertainty that depends on the quality or quantity of the available information (Akter and Simonovic 2005). The final type of uncertainty can be classified into numerical, linguistic, interval-valued and symbolic (Zimmerman 2001).

2.6.2.3 Proximity Analysis

Another important spatial quantification technique used in this study is the proximity analysis. This is a type of analysis in which geographic features (points, lines, polygons or raster cells) are selected based on their distance from other features or cells (Wade and Sommer 2006). Using spatial measurement of point-to-point distances, proximity has been used to determine the degree of interaction between two spatial entities (Lo and Yeung 2007). The Newton's law of universal gravitation has been influential in conceptualising proximity, which accordingly, two bodies attract each other in proportion to the product of their masses and inversely as the square of their distances apart (Haggett *et al.* 1977, Lo and Yeung 2007). This law has been applied to the study of population migration and retailing in human geography, spread of wildlife and insect infestation, timber harvest planning, wildlife habitat analysis, and dispersion of pollutants from a point source (Lo and Yeung 2007). Wood and Molloy (2009) developed a methodology using proximity analysis in landscape ecology for biodiversity planning and management in the South West Region, Western Australia.

Also known as neighbourhood, distance, and vicinity analyses (Davis 2001), the concepts and techniques of spatial calculation used in proximity are relatively simple and straightforward but their importance in vector processing and GIS application can never be discounted (Lo and Yeung 2007).

2.6.2.4 Quadrat Analysis

The use of quadrat analysis as a means of understanding object patterns is highly popular in ecological studies. A wide range of studies can be cited from literatures on the application of this analysis from microorganism level to giant sequoia tree like the works of Saetre and Baath (2000) and Bonnicksen and Stone (1980), respectively. Spatial pattern analysis was also explored in ophthalmology by Ayala *et al.* (2006) archaeology by Orton (1982) and traffic incidents by Eckley and Curtin (2013). In electronics, Miranda *et al.* (2011) examined quadrat counting method (QCM) by integrating Morishita index in the analysis of the spatial breakdown spots pattern in metal gate/magnesium oxide/indium phosphide structures and found complete spatial randomness of the structures.

Taken from the ecological perspective, association as a powerful indicator of interaction between species may be determined using quadrat sampling and plotless methods (Sanjerehei (2011). As the oldest method used in spatial statistics, quadrat sampling is efficient, easy to implement, and allows exhaustive sampling; however, less used for detecting association since the outcome of the association between species is dependent on the size and shape of the sampling quadrats (Sanjerehei 2011). Literatures cited that one major drawback of the quadrat counting method (QCM) is that the choice of the quadrat size is strongly linked to the spatial scale (Miranda *et al.* 2011). Despite a number of proposed methods to minimise this problem, statistical method still necessarily relies on the determination of an appropriate quadrat size and shape (Sanjerehei 2011).

2.6.2.5 Spatial Statistics with Collect Events Analysis

ESRI (2011) defined collect events analysis as a process of converting event data, such as crime or disease incidents, to weighted point data. Accordingly, this combines coincident points that have the same X and Y centroid coordinates. However, there is a very limited number of literatures exists which are directly involved in using coincident experiments. The statistical analysis for estimating the number of coincident events in electronic and radioactive decay constants conducted by Friedlander (1964) and the coincidence experiment for astrophysics analysing the coincident events between SPASE and AMANDA conducted by Miller *et al.* (1995) are examples of studies related to collect events analysis.

2.6.2.6 Modelling with Spatial Autocorrelation

A significant number of risk assessment methodologies for critical infrastructures had been established that adopting the linear approach (Giannopoulos *et al.* 2012). One of the types of infrastructure interdependency, other than physical interdependency, is geographic interdependency which Rinaldi *et al.* (2001) described as interdependency based on local environmental event (e.g. flood) that simultaneously affects several infrastructures due to close spatial proximity. In spatial science, spatial proximity of objects can be modelled by spatial autocorrelation techniques.

Essentially recognised as the nature of geography (Wong and Lee 2005), spatial autocorrelation examines the spatial ordering of geospatial data such that objects from locations near one another in space are more likely to be similar than objects from locations remote from one another (Lo and Yeung 2007). This principle is best explained by Tobler's First Law of Geography stating that "everything is related to everything else, but near things are more related than distance things" (Tobler 1970). A variety of studies can be associated to the application of spatial autocorrelation techniques such as multi-scale land use modelling (Overmars *et al.* 2003), exploring spatial dependence of cotton yield (Ping *et al.* 2004), examining forest insect outbreaks (Bone *et al.* 2013), identifying pollution hotspots of Pb in urban soils (Zhang *et al.* 2008), among others.

The magnitude of spatial autocorrelation or spatial association of geographic events can be measured in a global or local scale. The global measures of spatial autocorrelation describe the overall spatial relationship; while, local measures of spatial autocorrelation describe the regional variability of spatial relationship of the study area (Wong and Lee 2005).

2.6.2.7 Hot Spot Analysis

In combination with other statistical cluster analysis, a range of research applications can be attributed to the use of hot spot analysis such as employment assessment (Ceccato and Persson 2002), neighbourhood effects and voter turn-out (Sui and Hugill 2002), road accidents (Prasannakumar *et al.* 2011), and the multi-scale mapping of basin's fire burned areas and fire severity (Lanorte *et al.* 2013), among others.

Whilst the application of spatial autocorrelation techniques such as the global Moran's I and local Moran's I were significantly useful in this study, these analytical tools however provided spatial clustering of objects of uncertain number of classes for risk classification when applied to heritage sites (Espada *et al.* 2012). Consequently, classes of less than two bring uncertainty in assigning the ordinal values for the perceived flood risk during the assessment process. The hot spot analysis was then operationalised in this study to address this issue and applied in the exposure assessment of heritage sites.

2.6.2.8 Line Statistical Analysis

Line statistics calculates a statistic on the attributes of lines in a circular neighborhood around each output cell (ESRI 2011). The tool operates by finding the majority, minority, and median values are weighted according to the length of the line (ESRI 2011). This statistical tool is not well-cited in literature; however, its use cannot be understated in assessing the vulnerability of road infrastructure in this study.

2.7 Vulnerability Assessment of Critical Infrastructures for Interdependency Analysis

Critical infrastructures are essential to the proper functioning of the society. However, when these infrastructures are threatened by natural and man-made disasters, it takes a complex process to identify priorities and cost-effective protective measures. The necessity to understand geographically the risk associated with the integrated infrastructures and the involved vulnerabilities is one of the various methods to analyse the problem. This study was conducted to perform an initial step in identifying the risk due to 2010/2011 flooding for critical infrastructure protection.

Often called as lifeline systems (McDaniels *et al.* 2007; Wang *et al.* 2012), critical infrastructures refer to critical physical facilities (Stapelberg 2008), technological networks (Utne *et al.* 2011), and logical systems (Huang *et al.* 2014) that play major importance for public welfare (Kjolie *et al.* 2012). The modern society is highly dependent on the continuous services of critical infrastructures which include electricity supply (Kjolie *et al.* 2012), transport services, water supply, oil and gas, banking and finance, and ICT (information and communication technology) systems (Utne *et al.* 2011). Consequently, the breakdowns and disruptions in infrastructural services may cause direct and indirect impacts to population's health, safety, security, and economy (Johansson and Hassel 2010; Huang *et al.* 2014).

In order to optimise the uses of infrastructures while minimising damages during and post-flood events, there is a need to recognise that a particular infrastructure cannot properly function when other infrastructure on which it depends malfunctions. This is the concept that promotes cascade failure (Collins *et al.* 2011). On the other hand, common cause failure occurs when two or more infrastructure networks are disrupted at the same time either because they occupy the same physical space (known as geographic interdependency) or the widespread occurrence of the root problems such as floods (Rinaldi *et al.* 2001), earthquakes (Abdalla and Niall 2010), terrorist attacks (Lin and Fan 2010), among others. In Queensland, Australia, both cascade and common cause failures were experienced when essential services were disrupted due to failures of the infrastructure systems during the 2010/2011 floods.

In a survey of critical infrastructure interdependency modelling conducted by Pederson *et al.* (2006), however, geospatial interdependency modelling was excluded from their study. It was only then that the GIS-based geographic interdependency analysis was explored by Abdalla and Niall (2010) and Lin and Fan (2010) using earthquake and hypothetical terrorist attack, respectively. Using this approach of analysing infrastructure interdependency in a flood risk scenario had not been substantially explored. Nevertheless, whatever the cause of infrastructure breakdowns – terrorism, natural events, or unintentional human error – the methods of responding to, mitigating, and ideally preventing breakdown reoccurrences are based on a common approach: the coordinated use of geospatial information (GITA 2008).

In spite of the fact that GIS is widely recognised to deepen the risk analysis of critical interdependent infrastructures, the approach has given little attention (Rey *et al.* 2013). Hence, this study explored the GIS approach of understanding the critical infrastructure vulnerability and their interdependencies.

2.7.1 Application of Self-Organising Neural Network (SONN)

Section 2.6 postulated that addressing the issue on the sufficiency of indicating variables for inclusion in the flood risk assessment exercise remains a challenging task. The question, so to speak, was on how to evaluate the available indicating variables which were perceived to have a certain degree of direct correlation (pattern similarity) with flood risk; hence, identified to be potentially included for further analysis (i.e. weighted overlay) (Espada 2013b and 2013c). In other words, those indicating variables that exhibited dissimilar patterns with perceived level of flood risk were excluded as flood risk and climate adaptation capacity indicators. A type of Artificial Neural Network (ANN) known as Kohonen's Self-Organising Map (SOM) was applied to enlighten the issue through the operation of the topological cluster analysis of a 2-dimension self-organising neural network (SONN) (Espada 2013b and 2013c). The SONN analysis then served as the prerequisite of critical infrastructure vulnerability assessment and interdependency analysis.

Self-organising maps (SOM) mimic the action of a biological network of neurons, where each neuron accepts different signals from neighbouring neurons and processes them (Ballabio *et al.* 2009). Kohonen maps are self-organising systems which are capable to solve unsupervised rather than supervised problems (Kohonen

1988). As an effective tool for the visualisation of high dimensional data (Nourani *et al.* 2013), SOM allows to convert complex, nonlinear statistical relationships between high-dimensional data items into simple geometric relationships on a low-dimensional display while preserving the topology structure of the data (Kohonen 1997).

There are numbers of successful applications of self organising maps were reviewed from current literature such as in chemometry (Ballabio *et al.* 2009), categorisation of water, soil and sediment quality in petrochemical regions (Olawoyin *et al.* 2013), clustering spatial–temporal precipitation (Hsu and Li 2010), among others. In risk assessment, some studies include typhoon-rainfall forecasting (Lin and Wu 2009), detection of possible earthquake precursory electric field patterns (Ozerdem *et al.* 2006), modelling hydrologic and geomorphic hazards across post-fire landscape (Friedel 2011), and flood estimation (Dawson *et al.* 2006).

In terms of assessing variables, studies like stream modification patterns of a river basin (Jeong *et al.* 2010), assessing meteorological variables for evaporation estimation (Chang *et al.* 2010), and modelling for karst flood forecasting (Siou *et al.* 2011) were of significant contributions. However, the application of SOM/SONN to examine the indicating variables for flood risk and climate adaptation capacity assessments in relation to vulnerability assessment of critical infrastructures has never been explored as far as the review of literature by the author is concerned. Hence, the application of SOM/SONN to this study was explored as a decision-making tool in selecting the indicating variables to be included in the further analysis.

2.7.2 Application of Bayesian Joint Conditional Probability

Established under the *Commission of Inquiry Act 1950*, the Queensland Floods Commission of Inquiry (QFCI) was set up to enquire into matters arising out of the 2010/2011 floods (QFCI 2012). The Commission made recommendations for the improvement of preparation and planning for future floods and emergency response in natural disasters. Because disastrous floods which struck south-east Queensland in January 2011 were unprecedented and completely unexpected, governments should improve readiness to deal with disaster (QFCI 2012). Included in the Commission's recommendation is how can flood damage be minimised across essential infrastructures such as electricity, sewerage, storm water, telecommunications, and roads and rails in the future. The big challenge to implement these recommendations is the availability of spatially explicit analytical tools that will help the governments, industries, and people to prepare and adapt to climate risk and increase critical infrastructure resiliency (Espada *et al.* 2013b, 2013c).

In response to these recommendations, the development of flood risk and adaptation capacity metrics was considered in this study. However, developing a comprehensive set of metrics is challenging due to a wide variety of adaptations as well as the dynamic nature of various environmental and socio-economic factors (Szlafsztein 2008). This research problem is further exacerbated by inductive argumentation which particularly pertains to the sufficiency of indicating variables and availability of statistical models in climate risk assessment. When these indicating variables are aggregated with deductive approach (e.g. expert judgment) or by normative approach (e.g. equal weighting), the delivery of robust results is an issue due to subjective judgments in the former case and the multi-dimensionality of variables to different stakeholders in the latter case (Hinkel 2011).

There were various Bayesian probabilistic studies conducted to simulate uncertainty such as impacts of sea level rise on coastal engineering design practice (Rajabalinejad and Demirbilek 2013), flood frequency estimation (Niggli and Musy 2005, O'Connell 2005), and hurricane risk perceptions (Kelly *et al.* 2012), among others. The challenge of addressing the limitations of deductive and normative arguments in the flood risk and climate adaptation capacity assessments has never been substantially explored in accordance with the extensive review of literature. As such, varying degrees of importance (unequal weights) of flood risk and climate adaptation capacity indicating variables were generated using Bayesian probability. These probability values were instrumental in the weighted overlay operations in generating consequential hazards, physical vulnerability, and exposure indices. These indices were further utilised to quantify the flood risk and climate adaptation metrics using the fuzzy gamma overlay function.

The fuzzy gamma overlay operation was chosen in this study to resolve the confusion as to which risk equation (see Eq. 3.1 and 3.2) will be used in the assessment. This operation combined the "increasive" and "decreasive" effects of fuzzy "sum" overlay and fuzzy "product" overlay operations, respectively (Farrell *et al.* 2006). This mathematical framework emphasised that operating Eq. 3.1 in fuzzy logic rendered a limitation such that this equation was expressed neither just a mere "product" nor "sum" operation but extended to a "gamma" operation (Espada *et al.* 2012). Furthermore, the operation of those equations takes the parametric approach wherein data were used to build a picture of the vulnerability (and risk) of the study area (Balica *et al.* 2013).

2.7.3 Critical Infrastructure Interdependency Analysis

Critical infrastructures do not exist in isolation of one another (Rinaldi 2004), they consist of complex, highly connected and highly interdependent systems (Stapelberg 2008) and the failure of one infrastructure may impact the functionality of others (Huang *et al.* 2014). By definition, interdependency is a bidirectional relationship that exists between two infrastructures with each is dependent on the other (Rinaldi *et al.* 2001, Rinaldi 2004, Stapelberg 2008, Lin and Fan 2010). Highly useful in the vulnerability assessment, infrastructure interdependencies are taxonomically categorised into physical, informational/cyber, geospatial, and logical interdependency (Rinaldi *et al.* 2001; Dudenhoeffer 2006; Stapelberg 2008; Lin and Fan 2010).

A variety of studies had been conducted to examine the relationships of infrastructure interdependencies. The importance of complete and accurate baseline information and topological characterisation was emphasised in the studies conducted by Laefer *et al.* (2006) and Dueñas-Osorio *et al.* (2007) in analysing and understanding the geographic interdependency of critical networked infrastructures. As part of geographic interdependency modelling, Abdalla and Niall (2010) used location-based critical infrastructure interdependency (LBCII) in analysing the critical infrastructure sectors that were co-located and affected by an earthquake scenario. Further, an empirical framework for characterising infrastructure failure interdependencies for power system outages was developed by McDaniels *et al.* (2007).

Traditionally, flood risk management had been implemented to protect people and property and reduce the disastrous effects of flooding to essential infrastructures. In the past years, increasing resiliency for infrastructure such as electricity, water supply, telecommunication, transportation, and among others, had been treated separately. Focusing on one's own facilities and pay little attention to cross system interactions complicates issues on infrastructure interdependency (Chou *et al.* 2007). Further, individual approaches do not address the interconnected relationships between these infrastructures and therefore do not provide a comprehensive approach. Hence, comprehensive understanding of all interdependency relationships remains a challenging task (Chou and Tseng 2010).

Following the concept of utility network, the infrastructure components that build up the system are defined into two: nodes (e.g. electricity supply stations) and edges (e.g. electricity transmission lines) (Johansson and Hassel 2010). Moreover, the functional and geographic interdependency models were advocated by Johansson and Hassel (2010) to be incorporated in the network model. In implementing their theory into practice, this study explored the vulnerability of an infrastructure from functioning properly (e.g. power outage) through utility network analysis given the geographical locations of its nodes and edges across areas characterised by very high flood risk or low climate adaptation capacity.

From the extensive review of literature, approaches used in analysing infrastructures were diverse, but, the pattern was to firstly need to find out the vulnerability and interdependency of critical infrastructure system (CIS), then use a kind of methods to quantify them, and implement corresponding measures (Li and Huang 2010). This study adopted these general steps, but, with a novel approach by utilising a combined set of self-organising neural network, Bayesian probability, and utility network analyses.

2.8 Optimisation Techniques with Markov Decision Process

Markov Decision Process (MDP) relies on theory to model feasible action with associated transition matrix containing the probabilities that performing the action in state *s* will move the system to state *s'* (Schapaugh and Tyre 2013). As a stochastic process, MDP is a decision-making model for finding optimum policy under certainty (White III and White 1989; Eun-Kim 1994; Dufour and Prieto-Rumeau 2014). For examples, Krougly *et al.* (2009) presented a stochastic model simulating fire behaviour in a forested landscape and illustrated the total disturbance impact under different initial conditions and scenarios. In Tianjin coastal area, China, Ma *et al.* (2012) used Markov chain as a stochastic model in assessing wetland change dynamics and demonstrated three main conclusions: 1) a continuing 'exchange' of wetland area occurs between artificial wetlands and natural wetlands categories; 2) pollution and construction were the predominant causes for wetland changes; and 3) the natural wetlands will be in great decline in 2020 and 2050.

There were also numbers of studies conducted for modelling decision-making problems in different areas, such as finding optimum hydro-power production (Lamond and Boukhtouta 1996), maintenance policy of repairable power equipment (Tomasevicz and Asgarpoor (2009), inventory control problem for optimal ordering decisions (Ahiska *et al.* 2013), and natural resources conservation and management (Williams 2009). In rangeland management, for example, Freier *et al.* (2011) investigated a dynamic land use decision model using Markov chain meta-model and revealed two significant results: 1) the drought simulations show a decrease in profits from pastoralism by up to 75%; and 2) pastoral land use of the rangeland increases surface runoff by 20%, doubles infiltration, and thus influences irrigation agriculture.

Moreover, urban growth modelling with Multi-Criteria Evaluation framed in Markov Cellular Automata model (Vaz *et al.* 2012) and simulation through Markov analysis on the land use, and effects of urban, agricultural, forest and wetland dynamics (Vaz *et al.* 2013) are some analytical tools used in assessing the consequences of regional environmental changes. Integrated with GIS, those studies revealed a set of promising tools for the strategic development of rural and/or urban areas in response to environmental challenges arising from exploitation of land-use resources, economic prosperity, increasing population, growth of infrastructures (Vaz *et al.* 2012), and natural disasters.

In a study conducted by Arsanjani *et al.* (2013), they analysed the suburban in the metropolitan area of Tehran, Iran by using the hybrid model consisting of logistic regression model, Markov chain, and cellular automata. They found a satisfactory performance to predict land use maps for 2016 and 2026 illustrating a new wave of suburban development for the next decades. In Mumbai, India, Moghadam and Helbich (2013) implemented an urban growth model by integrating Markov Chains-Cellular Automata (MC-CA) that characterised the open land and croplands having mostly affected by degradation. Further, their forecast revealed that built-up areas will increase by 26% in 2020 and 12% in 2030 and mostly pronounced toward the north along the main traffic infrastructure and eastern areas. Similar trend was observed in a study conducted by Guan *et al.* (2011) that built-up areas in Saga, Japan will undergo an upward trend affecting agricultural land and forestland areas. This was further supported in the study conducted by Haibo *et al.* (2011) in Tai'an City, China wherein the Markov model revealed that farmland was mainly changed to lawn or residential land. Agricultural expansion is the main driving force for loss of forest, wetland and marshy land and has the potential to continue in the future (Behera *et al.* 2012).

Xin *et al.* (2012) compared the performance of MC-CA model with Ant Colony Optimisation-Markov Chain-Cellular Automata (ACO-MC-CA) model in the spatiotemporal assessment of land use change in Beijing, China. The latter revealed a promising result being more appropriate to use in predicting the quantity and spatial distribution of land use change in the study area (Xin *et al.* 2012). Within the same city, Wang *et al.* (2012) explored the accuracy of MC-CA simulation through the calculation of Kappa index for location and quantity. Their analysis revealed that simulation accuracy of small cell size is better than big cell size which gives a better understanding on how to select best spatial resolution for simulation. In order to grip land use changes better, Sang *et al.* (2011) proposed that simulation can be divided into two parts: one is the quantitative forecast by using the Markov model, and the other is the simulating the spatial pattern changes by using the CA model. Validating the performance of CA-Markov model, statistics revealed that accuracy is slightly higher when this model is combined with multi-objective land allocation (MOLA) procedure in the land use and land cover (LULC) change analysis (Surabuddin *et al.* (2013). In 2009, the Markov-CA-MOLA procedure was used in simulating future land use/cover changes (up to 2030) and predicted a continuing downward trend in woodland areas and an upward trend in bare land areas (Kamusoko *et al.* 2009). To reduce bias in the non-spatial error term of those models, Finley *et al.* (2009) offered a knot-based predictive process approach set in the Markov chain Monte Carlo models.

We further examined the application of Markov models in natural disaster risk reduction. The binomial cluster analysis and MDP were used in optimal-decision making such as the identification and selection of disaster debris management sites (Grzeda 2014) and optimum utilisation of open space for emergency response (Li *et al.* 2013), respectively. The Markov-CA-MOLA procedure was used in Nigeria to predict the areas where desert conditions are likely to spread to by the year 2030. Musa *et al.* (2012) emphasised that the valleys of the Rivers Kamandagu Gana and Kamandugu Yobe are among the most vulnerable areas from desertification. Applied in the vegetation restoration assessment at landslide areas caused by catastrophic earthquake in Central Taiwan, the Markov-chain model showed that vegetation restoration at the Chiufenershan and Ninety-nine peaks landslide areas is ongoing, but has been disturbed by natural disasters (Chuang *et al.* 2011). In modeling emergency evacuation for major hazard industrial sites, Georgiadou *et al.* (2007) used the Markov-Monte Carlo model to support decisions for emergency response concerning for example areas that must be evacuated or not in certain circumstances and for land use planning issues such as providing information about the need to increase transportation network capacity and safe shelters.

Having reviewed pertinent literature, the studies on optimising expenditures for natural disaster risk reduction have never been substantially explored. In doing this study, we introduced a new way of dealing with uncertainty in the state transition function by using existing records on government expenditures for natural disaster risk reduction measures, social discounting factors, and total business loss during the January 2011 flood in the study area within the MDP framework. The authors acknowledged that this study is a rare situation in natural disaster risk management to implement in an urban area. Markov analysis is spatially non-explicit (Lopez *et al.* (2001); Moghadam and Helbich 2013); however, this study explored on how to transform the model become spatially explicit and applied in identifying optimal decisions and policy actions for flood mitigation.

2.9 Summary

The overall issues of the current flood risk and climate adaptation capacity techniques in relation to the vulnerability assessment of critical infrastructures and interdependency are outlined as follows:

- Separate frameworks for flood risk and climate adaptation capacity assessments currently exist which in reality both have the same goal – disaster risk reduction from extreme climatic events;
- Available spatial datasets for flood risk and climate adaptation capacity indicating variables vary in formats from different sources;
- Selection and integration of indicating variables to be included in the flood risk and climate adaptation capacity assessments for vulnerability assessment of urban community and critical infrastructures are currently not clearly defined;
- Analysis of critical infrastructure interdependency for disaster risk reduction or climate adaptation in GIS setting has never been substantially explored; and
- In a highly competitive financial environment, optimisation techniques need to be operationalised to prioritise funding support for natural disaster risk reduction and climate adaptation.

These issues defined the overall framework and nexus amongst flood risk, climate adaptation capacity, critical infrastructure interdependency, and natural disaster risk reduction.

Chapter 3

METHODS FOR THE TRANSFORMATION AND STANDARDISATION OF INDICATING VARIABLES

3.1 Introduction

This Chapter outlines the transformation and standardisation techniques used in developing the preliminary indices of flood risk and climate adaptation capacity. The significant contributions of this Chapter in the study are the applications of various spatially-explicit analytical tools which account the multi-dimensionality of geographic variables. These include the use of high resolution LiDAR dataset in the flood hazard analysis, fuzzy logic, spatial autocorrelation techniques, and other spatial statistics especially designed to represent flood risk and climate adaptation capacity indicating variables.

As a common practice in GIS, flood and climate risk assessments require a set of analytical tools which allow the indicating variables for hazard, vulnerability and exposure be transformed and standardised into a uniform set of representation. This is because the identification of potential risk indicators is essential for effective disaster planning otherwise sensible mitigation measures cannot be fully developed and effectively implemented without undertaking a meaningful analysis (Eckert 2012). As the popular maxim states: “what cannot be measured, cannot be managed.”

To empirically support the selection of indicating variables as presented in Table 3.1, this Chapter examined a set of literature aside from those presented in Chapter 2 (Literature Review). One of the major thematic elements in flood hazard mapping is the Digital Elevation Model (DEM). DEM data have been used to derive hydrological features which serve as inputs to various models (Li and Wong 2010) such as the flood hazard model. This study used the DEM based on airborne light detection and ranging (LiDAR) in the flood hazard modelling because of high horizontal resolution, vertical accuracy (~0.1 m) and the ability to separate bare-earth from built structures and vegetation (Sanders 2007). With specific attention given to the January 2011 flood, major flood characteristic such as area of inundation (Yu *et al.* 2009) was incorporated into the DEM database to characterise or measure the degree of flood hazard.

Injuries can occur before, during and after flood; however, the most common reasons for flood-infected nonfatal injuries are cuts, falls, being struck by falling debris or objects moving quickly in flood water (Alderman *et al.* 2012). Increased risk for water- and vector-borne diseases and exposure of population to toxic chemicals can also be associated to floods (Alderman *et al.* 2012). In this study, biological hazard (e.g. microbes from debris and sewerage), chemical hazard (e.g. presence of asbestos), electricity hazard (e.g. power boards submerged under water), and building damage/collapse hazard were taken from the Queensland Fire and

Rescue Services (QFRS) database. These data were collected through the agency's rapid damage assessment during the January 2011 to assess damage to properties (DCS 2011).

Adger (2006) defined vulnerability as the state of being susceptible to harm from exposure to stresses associated with physical environment and social conditions and from the absence of capacity to adapt. Based on this concept, a variety of studies identified the following generic indicators of vulnerability which serve as the basis in the selection of indicating variables for vulnerability in this study (Brooks *et al.* 2005, Marshall *et al.* 2014, Ahsan and Warner 2014, Lee 2014):

- Percentage of old and children
- Literacy rate
- Civil liberties
- Voice and accountability
- Political rights
- Government effectiveness
- Employability
- Family
- Business size and skills
- Financial status and access to credit
- Income diversity
- Local environmental knowledge
- Environmental awareness
- Formal and informal networks
- Connection to infrastructure services (electricity, water, transportation, etc.)
- Access to public infrastructure and security (e.g. emergency infrastructures).

UNDP (2004) defined exposure as the inventory of those people or artefacts that are exposed to a hazard. In characterising the indicating variables for exposure, this study considered the following exposure indicators as the guide in the selection of datasets (Moel *et al.* 2011, Belmonte *et al.* 2011):

- Total amount of urban area that can be potentially become inundated due to floods. This includes number of population, highly vulnerable critical infrastructures and culturally significant assets;
- Level of human and critical infrastructure exposure to flood.

The specific methods of data standardisation and transformation for the hazard, vulnerability, and exposure indicating variables are fully explained in Section 3.3.

3.2 Key Concepts and Data Inputs

In Chapter 2, the concept of risk was established as a function of hazard, vulnerability, and exposure. Expressed in mathematical forms, risk can be stated as (Mirfenderesk and Corkill 2009; Downing 2002; Hughey and Bell 2010):

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Exposure} \qquad \text{Eq. 3.1}$$

$$\text{Risk} = \text{Hazard} + \text{Vulnerability} \qquad \text{Eq. 3.2}$$

Risk = Hazard + Vulnerability – Adaptation Capacity Eq. 3.3

As shown in these equations, the terms hazard, vulnerability, exposure, and adaptation capacity are significantly associated to each other and can influence the flood risk assessment process. The fuzzy gamma overlay operation was chosen in this study to resolve the confusion as to which risk equation (see Eq. 3.1 and 3.2) will be used in the assessment. This operation combined the "increasive" and "decreasive" effects of fuzzy "sum" overlay and fuzzy "product" overlay operations, respectively (Farrell *et al.* 2006). Furthermore, the operation of these equations takes the parametric approach wherein readily available data were used to build a picture of the vulnerability (and risk) of the study area (Balica *et al.* 2013). In the absence of sufficient and reliable data on future and residual risks in relation to the flooding events within the study area, this study mainly focused on existing or current flood risk using the fuzzy gamma overlay operation.

By transforming Eq. 3.3, adaptation capacity can be mathematically expressed as follows (Espada *et al.* 2012):

Adaptation Capacity (AC) = Vulnerability – (Risk + Hazard) Eq. 3.4

To operationalise Eq. 3.4, it has been further expressed in Equations 3.5 and 3.6.

AC = Social Vulnerability – (Risk + Flood Hazard) Eq. 3.5
AC = Social Vulnerability – [(Fuzzy Gamma Function {Consequential Hazards, Physical Vulnerability, and Exposure} + Flood Hazard)] Eq. 3.6

Table 3.1 summarises the list of thematic layers/indicating variables used to analyse the components of flood risk and adaptation capacity. The significance of identifying and understanding these indicating variables relates to the findings of the inquest into the January 2011 south-east Queensland flood deaths. Pursuant to s8(3)(b) of the Coroners Act 2003, for example, one amongst 22 known reportable deaths was identified as Ms. S.H. Baillie. Died in Postman Ridge, Queensland, Australia, Ms. Baillie, 72 years old, was the sole occupant of a single-storey brick house situated 10 to 20 meters from the banks of Rocky Creek (Barnes 2012). The house had collapsed and was swept away by a wall of water during a flash flood that caused her death from drowning (Barnes 2012). Given these actual circumstances, the age, number of occupants, proximity to river, and building type and density were the potential indicating variables that explain the observed harm from the flood event.

Table 3.1 The thematic layers/indicating variables with corresponding assumptions used in the study

Risk Component	Indicating Variable	Assumption	Input Data Source
Hazard	Defined Flood Level (DFL) and 2011 Flood Extent	Defined Flood Level (DFL) and 2011 flood extent indicate the observed harm from extreme weather or climate event to the urban community and critical infrastructures.	BCC, DERM and QGIS;
	2009 Digital Elevation Model (m)	Flooded elevation indicates the observed flood hazard of the area. The areas with low DEM values indicate high flooded areas.	LIDAR data from DERM
	Biological Hazard	Biological hazard, building damage hazard, chemical hazard, and electricity hazard were observed second level processes or agents (consequential hazards) which indicate harm as	QFRS
	Building Damage Hazard		QFRS
	Chemical Hazard		QFRS

Risk Component	Indicating Variable	Assumption	Input Data Source
	Electricity Hazard	results of flood event.	QFRS
Physical Vulnerability	Building Floor Space	Areas with higher building floor space index generally indicate lower physical vulnerability to flood hazard.	DERM; ArcGIS Online
	Estimated Period of Settlement (No. of Years between 1800 to 2011)	Areas earlier settled with significant growth in residential, industrial and commercial activities have likely older buildings than other areas; hence, relatively more vulnerable from wear-and-tear and require higher investment for retrofitting, maintenance and improvements.	BCC, ABS and UQ-CGQ
	Electricity Assets	Areas holding critical electricity assets (e.g. zone supply substations, transformer sites) may indicate high physical vulnerability to flood damage.	Energex
	Roads and Rail	Areas with highly flooded roads and rail networks may indicate high physical vulnerability to flood damage.	QGIS
	Sewerage	Areas holding critical sewerage assets (e.g. pump stations, storage facilities, and wet well) may indicate high physical vulnerability to flood damage.	BCC
	Stormwater	Areas holding critical stormwater assets (e.g. stormwater SQID – gross pollution trap and sediment trap, and pipe outlets) may indicate high physical vulnerability to flood damage.	BCC
	Water Supply Network Assets	Areas holding critical water supply assets (e.g. water pressure main, valves, water devices and hydrants, and water service equipment) may indicate high physical vulnerability to flood damage.	BCC
Social Vulnerability	2011 Population by Age (0-14 and > 65 in %)	Areas occupied by higher percentage of population with ages 0 to 14 and above 65 generally indicate higher degree of social vulnerability to flooding and consequential hazards.	ABS and BCC
	2010-2011 Total Counts of Registered Businesses (No.)	Suburbs with higher counts of registered businesses indicate higher revenue; hence, lower degree of social vulnerability than suburbs with lower counts.	ABS and BCC
	2011 Educational Qualification (%)	Suburbs with higher proportion of persons with educational qualification (i.e. bachelor degree or higher, diploma, and certificate) indicate a lower degree of social vulnerability.	ABS and BCC
	Access to Emergency Services	Far distance and long response time from emergency services (i.e. police stations, hospitals, fire and rescue, and evacuation centres) generally indicate relatively high degree of social vulnerability to flood event and consequential hazards.	Google Earth
	Emergency Response Time		
	2011 Index of Education and Occupation (IEO)	Suburbs with higher index score indicate relatively higher education and occupation status of people in general; hence, more advantageous with less degree of social vulnerability than in other suburbs.	ABS
	2011 Index of Economic Resources (IER)	Suburbs with higher index score indicate relatively greater access to economic resources related to income and wealth in general; hence,	ABS

Risk Component	Indicating Variable	Assumption	Input Data Source
Social Vulnerability		more advantageous with less degree of social vulnerability than in other suburbs.	
	2011 Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD)	Suburbs with higher index score indicate lower disadvantage and greater advantage in general in relation to the economic and social conditions of people and households; hence, more advantageous with less degree of social vulnerability than in other suburbs.	ABS
	2011 Index of Relative Socio-Economic Disadvantage (IRSD)	Suburbs with higher index score indicate lower disadvantage in general in relation to the economic and social conditions of people and households; hence, lower degree of social vulnerability than in other suburbs.	ABS
	2012 Insurance (Home and Content) ($)	Areas with higher average sum of insurance premium are more likely flood-prone areas; hence, higher degree of social vulnerability to flood hazard than other suburbs.	Suncorp Insurance
	2011 Persons in Need of Assistance (%)	Areas with the higher proportions of people in need of assistance indicate areas with relatively profound or severe disability; hence, a higher degree of social vulnerability.	ABS and BCC
	2011 Without Vehicles (%)	Areas with larger percentage of occupied private dwellings with no motor vehicles indicate lack of immediate mobility during emergency; hence, a higher degree of social vulnerability.	ABS and BCC
	2011 Residential Tenure - Renting (%)	Higher percentage of rented private dwellings generally indicate lack of property ownership in the area in general; hence, a higher degree of social vulnerability.	ABS and BCC
	2012 Total Building Value ($'000)	Suburbs with higher recorded total value of residential and non-residential buildings indicate areas with higher valuable assets; hence, lower degree of social vulnerability.	ABS and BCC
	2012 Unemployment Rate (%)	Suburbs with higher proportions of unemployed persons aged 15 years and over indicate areas with lower income; hence, higher degree of social vulnerability.	ABS and BCC
	2011 Volunteers (%)	Suburbs with higher percentage of volunteers aged 15 years and over indicate areas with higher accessibility to social assets; hence, lower degree of social vulnerability.	ABS and BCC
	2011 Weekly Personal Income (%)	Suburbs with higher percentage of persons aged 15 years and over who had their total personal weekly income less than $400 per week may indicate higher degree of social vulnerability.	ABS and BCC
Exposure	2011 Flooded Residential and Commercial Properties (No.)	Suburbs with high number of flooded residential and commercial properties during the January 2011 flood are likely more exposed to flood hazard than other suburbs.	Houghton, *et al.*, 2011
	Heritage Sites	Heritage sites highly clustered together may indicate relatively highly exposure of cultural assets to flood hazard.	DERM
	2011 Estimated Resident Population (No.)	Areas with higher number of estimated resident population indicate a higher number of people exposed to flood hazard.	ABS and BCC
	2007-2011 Average Annual	Areas with higher percentage of annual population growth rate indicate a higher change	ABS and BCC

Risk Component	Indicating Variable	Assumption	Input Data Source
Exposure	Population Growth Rate (%)	in population over a unit time period; hence, relatively greater exposure of number of people to flood hazard.	
	Electricity	Areas holding higher number of pole assets providing direct source of electricity to residents indicate relatively greater exposure to flood hazard.	BCC
	Sewerage	Areas holding higher number of main reticulation inlets providing direct sewerage services to residents indicate relatively greater exposure to flood hazard.	BCC
	Stormwater	Areas holding higher number of stormwater gully inlets where garbage/solid wastes may potentially clogged indicate relatively greater exposure to flood hazard.	BCC
	Water Supply Connections/ Services	Areas holding higher number of water supply assets providing direct water connections or services to residents indicate relatively greater exposure to flood hazard.	BCC

ABS – Australian Bureau of Statistics; BCC – Brisbane City Council; DERM – Queensland Department of Environment and Resource Management; QFRS – Queensland Fire and Rescue Service; QGIS – Queensland Government Information Service; UQ-CGQ – University of Queensland Centre for Government Queensland

3.3 Data Transformation and Standardisation

The development of indices for flood risk and climate adaptation capacity is a daunting task particularly when it involves datasets that are represented in varying formats. As outlined in Table 3.1, it is evident that this study used available data from various sources presented in different spatial information (i.e. tabular, vector and raster), units of measurement (e.g. meters, per cent, index, etc.) and geographic features (i.e. points, lines, and polygons). For this reason, this study identified some spatially-explicit analytical tools that allowed the construction of standardised food risk and climate adaptation capacity indices in a uniform raster format. These analytical tools include:

1) digital elevation modelling (DEM) and urban morphological characterisation with 3D analysis;
2) spatial analysis with fuzzy logic;
3) proximity analysis;
4) quadrat analysis;
5) spatial analysis with collect events analysis;
6) geographic interdependency modelling with spatial autocorrelation;
7) hot spot analysis; and
8) line statistics.

Except for those indicating variables that were available immediately in desired raster format, the application of these tools was not mutually exclusive in this study. Hence, the method was consequently designed to consider jointly performed with its cross-functional process shown in Figure 3.1. This diagram shows the cross-functional process map used in this study which outlines the means or the processes (shown in the "process" window) involved in the generation of perceived level of flood risks (the "end" or output window) which were derived from the indicating variables (shown from the "start" window). Part of the processing component was the definition of map datum, coordinate system, and UTM zone. The maps used in this study were defined based on Geocentric Datum of Australia 1995 (GDA 1994) with Map Grid Australia (MGA) as the coordinate system and 56 as the UTM zone.

The desired outputs which represent the flood risk and climate adaptation capacity indices were spatially-structured in raster format described in Table 3.2. This means that when generated indices are equivalent to 4 and 1, for example, risk is described as very high and adaptation capacity is low, respectively.

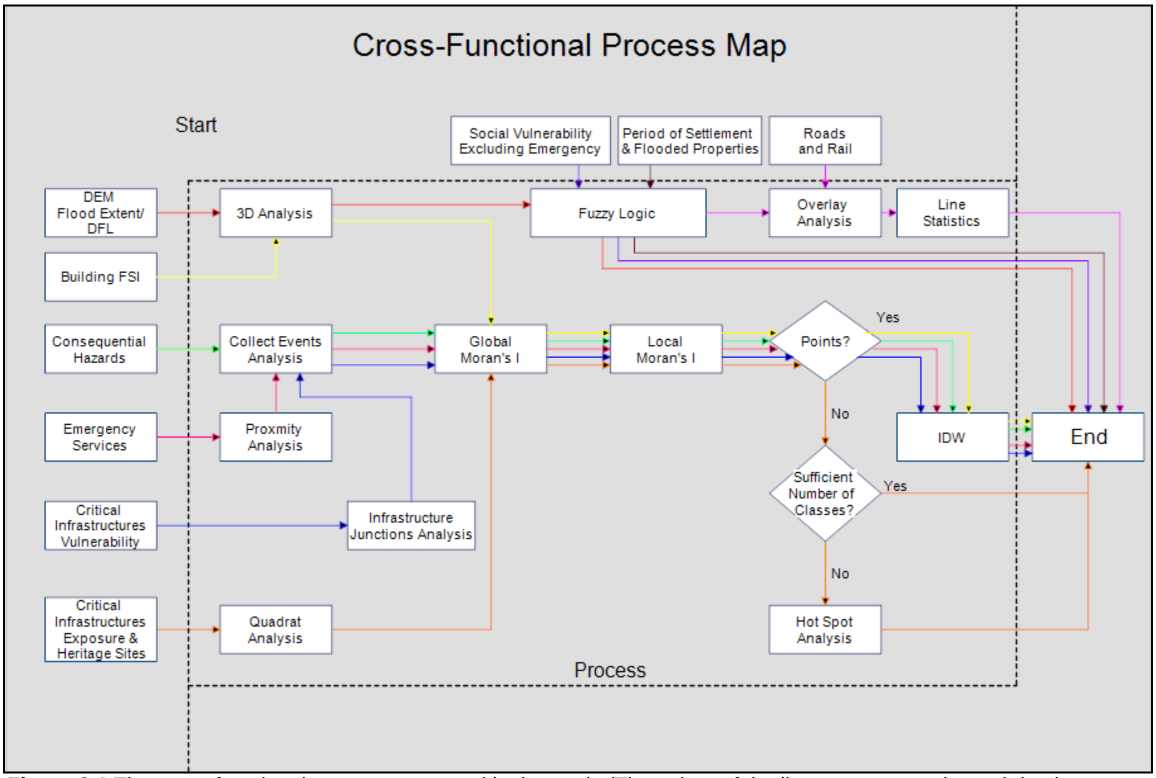


Figure 3.1 The cross-functional process map used in the study (The colour of the lines represents the path it takes to perform the data transformation and standardisation of indicating variables)

Table 3.2 Flood risk and adaptation capacity index classification

Risk Index	Description	Adaptation Capacity Index
1	Low	4
2	Moderate	3
3	High	2
4	Very High	1

The indexing system specified in Table 3.2 was adopted in this study to show flood risk and climate adaptation capacity at different intensity levels. These index designations were assigned following the concepts introduced by Balica *et al.* (2013). Accordingly, a very high designation is assigned if there is very high potential for loss of life and/or extreme economic loss based on indicators (e.g. hazard, vulnerability, and exposure). On the other hand, a low designation is assigned if there is a small but still existing potential for loss of life and the economic loss is minor (Balica *et al.* 2013). This means that a higher value of index data coincides with higher flood disaster risk (Jiang *et al.* 2009). These designations are a critical parameter without which disaster risk assessment (and climate adaptation capacity) cannot be calculated (Deichmann *et al.* 2011).

3.3.1 Three Dimensional (3D) Analysis

The 3D analysis was performed in this study in two ways: digital elevation modelling (DEM) for flood hazard analysis and digital building modelling (DBM) for urban morphological characterisation. The flowchart is provided below for guidance with full discussions presented in the subsequent sub-sections.

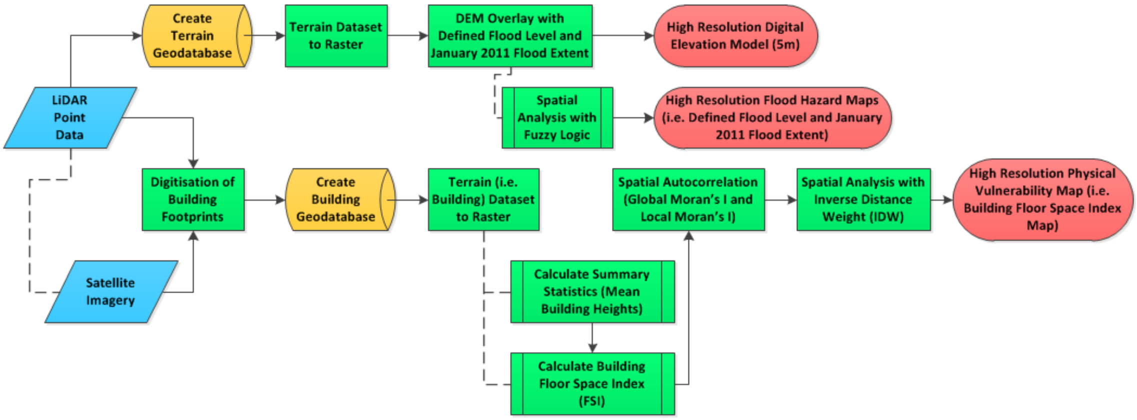


Figure 3.2 The flow chart of flood hazard analysis and urban morphological characterisation used in the study

3.3.1.1 Digital Elevation Modelling for Flood Hazard Analysis

Being traversed by a 345-kilometre Brisbane River, the study area shown in Figure 1.1 fits within the floodplain areas of the Brisbane catchment. As discussed earlier, Brisbane City had been devastated by the January 2011 flood and damaged thousands of infrastructures and residential and commercial properties. In 2009, the City has been part of the Queensland government-initiated project, i.e. the South East Queensland LiDAR Capture Project. The purpose of the project was to provide highly accurate elevation data for use in risk assessment, the management of natural disasters, infrastructure planning, and developing strategies to support climate change, topographic mapping and modelling (DERM 2011).

As a product of an aerial survey company and made available in 1 kilometre tile for use in this study, the airborne LiDAR data was captured in 2010 from a fixed wing aircraft with the technical background information summarised in Table 3.3. The laser (LAS – binary file format) strikes were classified into ground and non-ground points using a single step algorithm with classification format in accordance with ASPRS Standard LiDAR Point Classes as follows (DERM 2011):

2 – Ground
6 - Building
8 - Model Key-Point (Mass Point)
10 - Non-ground

One of the critical steps in generating Digital Elevation Model (DEM) from LiDAR point data is separating ground points from non-ground points by using a technique commonly known as filtering method. Over the past years, several widely recognised filtering algorithms had been developed to automate the extraction of ground points from non-ground points which include the interpolation-based filter, slope-based filter, and morphological filter (Liu 2008). The different applications of these filtering methods were comprehensively discussed in the works of Kraus and Pfeifer (1998), Vosselman (2000), and Kilian *et al.* (1996) and Lohman *et al.* (2000). As an active area for research, several filtering methods are currently underway on its development.

Using the ground classification value (i.e. 2) as enumerated earlier, the LiDAR points in LAS format was imported into multipoint ground feature class in ArcGIS 10 platform through the 3D Analyst tool. This was an automated scheme of searching filtered ground points for terrain modelling.

Table 3.3 The technical background information of LIDAR system and data (DERM 2011)

LASER Characteristic	LASER Description
Device Name	ALTM Leica ALS50-II
Flying Height	1700 m (Average)
Side Overlap	25% (Average)
Swath Width	850 m (Average)
Laser Footprint Size	0.34 m (Average)
Laser Mode	Multi-Pulse
Captured Terrain Model (All Laser Strikes)	2.5 points/m^2 (Average)
Supplied Terrain Model (All Points)	2.0 points/ m^2 (Average)
Ground Points (Open Clear Ground)	2.0 points/ m^2 (Average)
Project Area Average	0.7 point/ m^2 (Average)
Reference System	
Datum	GDA 94
Projection	MGA Zone 56
Vertical Datum	AHD
Geoid Model	Ausgeoid98
Accuracy	
Vertical Data (Derived Points)	0.15 m
Horizontal Data (Measured Points)	< 0.31 m
Tested Points (Measured Points)	0.05 m

Digital elevation models (DEMs) are usually represented in three ways: (1) grid DEM, (2) triangular irregular network (TIN), and (3) contour line model (Liu 2008). This study explored grid DEM by using the multipoint ground feature interpolated with the Inverse Distance Weight (IDW) technique. Almost all the LiDAR-derived DEMs had been produced using grids (Lohr 1998, Wack and Wimmer 2002, Lloyd and Atkinson 2006, Liu *et al.* 2007) from IDW interpolation primarily because the latter works well in highly dense and evenly-distributed sample points such as LiDAR (Childs 2004). The IDW method of interpolation is discussed separately in details in the subsequent section.

Raster DEMs were then produced by processing large LiDAR point collections using the geoprocessing tools known as “Point to Raster” and “Terrain to Raster” in ArcGIS platform. The advantage of using Point to Raster is the speed and convenience of processing; however, it does not produce the highest quality result possible (ESRI 2010). On the other hand, the use of Terrain to Raster gives higher quality results than Point to Raster particularly when the LiDAR point data are dealing with photogrammetric breaklines such as the edges of rivers, lake shorelines, and water-related features (ESRI 2011). To generate the 5m grid DEM as shown in Figure 3.3, this study opted to use the Terrain to Raster as the method of interpolation.

After generating the DEM, the identification of flood prone areas by delineating flood hazards (and risks) was the next step. Hence, the generated terrain model was processed and analysed further to generate the standardised flood hazard index. The task was challenged to find the locations from the DEM the maximum raster elevation (MaxREV) which will capture the areas that had been completely flooded.

Generally, the issue can be resolved by using either of the two methods: probabilistic approach or deterministic approach. The former involves estimating the flood flow quantiles in different predicted probabilistic scenarios by frequency analysis such as the work of Sarhadi *et al.* (2012). On the other hand, the deterministic approach, also called scenario-based, uses realistic scenarios for inundation based on historical data (Eckert 2012). This study used the deterministic approach by overlaying the January 2011 flood extent with the DEM.

Using the “Clip Raster Processing” tool in ArcGIS 10, the generated MaxREV was 11.94m. The area covered within the MaxREV down to the minimum raster elevation (MinREV), i.e. 11.94 to -23.57m, was identified as very high risk. Beyond the MaxREV, with elevation values between 11.95 to 83.76m, the flood hazard was assumed to diminish from high to low. Based on these elevation values and inference rules, the fuzzy linear membership function was operationalised to transform and standardise the elevation values into new fuzzy membership values ranging from 0 to 1. These new values defined the possibility of membership to a specified class or set, with 0 holding areas of very high flood risk and 1 of low flood risk as shown in Figure 3.4. To conform to GIS norms, the fuzzy membership values were further “refuzzified” using the fuzzy “small” membership function to reclassify 0 as low flood risk and 1 very high flood risk using 1 and 4 as flood hazard indices, respectively as summarised in Table 3.4.

A separate section is provided in this Chapter discussing in details about the use of fuzzy logic in data transformation and standardisation.

Table 3.4 The flood hazard categories and risk description

Elevation (m)	Fuzzy Membership Value	Flood Hazard Category	Risk Description
-23.57 – 11.94	0	4	Very High
11.94 – 25.25	0 - 0.27	3	High
25.25 – 41.67	0.27 – 0.49	2	Moderate
41.67 – 83.76	0.49 – 1	1	Low

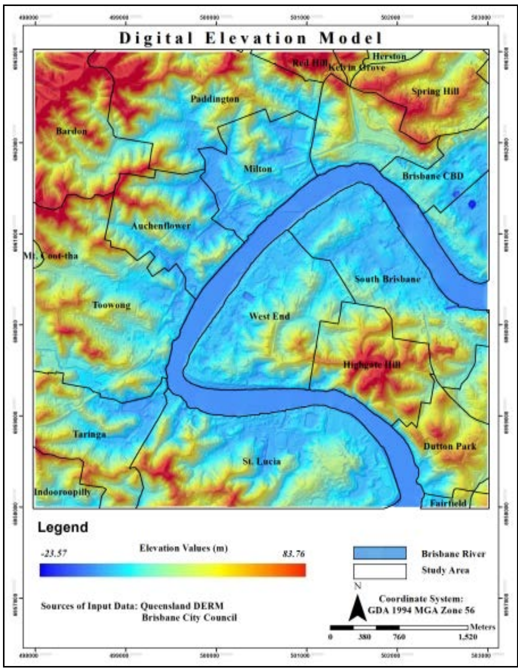


Figure 3.3 The LiDAR-derived digital elevation model

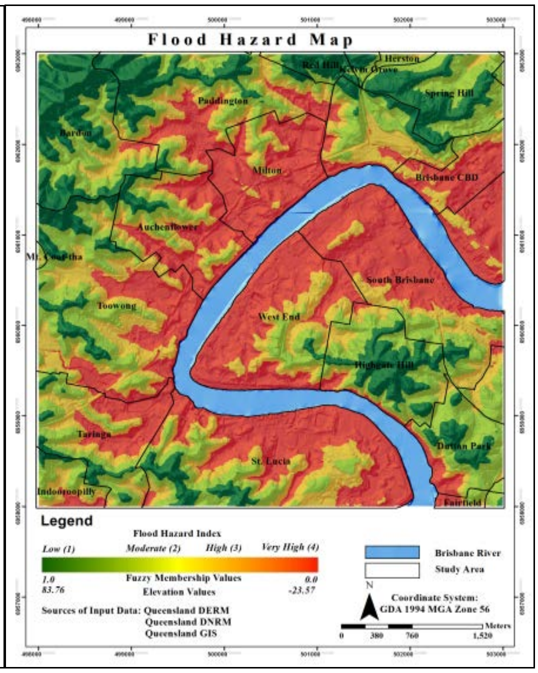


Figure 3.4 The flood hazard index map

3.3.1.2 Digital Building Modelling (DBM) for Urban Morphological Characterisation

This section presents a method of integrating the high resolution satellite imagery and LiDAR point data for generation of digital building model (DBM) and building floor space index (FSI).

One of the commonly used morphological variables to characterise urban fabrics is density which can be described based on ground space index (GSI) and floor space index (FSI) of the buildings. Opted to use the latter in this study, building FSI was calculated by using the buildings' space area and height parameters and mathematically operationalised as the ratio between the building volume and the corresponding Voronoi diagram's cell area (Hamaina *et al.* 2012).

Aimed to generate an object-oriented data structure, edges of almost 17,000 building objects were digitised on top of LiDAR point data and high resolution (1 meter or better) satellite and aerial imagery from ArcGIS Online. The main advantage of using this method was the attainment of high building footprints accuracy by detecting and excluding building walls which had been erroneously depicted by LiDAR points as part of building roofs. However, the method was tedious and time-consuming. The extracted edges of building objects with associated bi-dimensional geometric property and planimetric coordinates were saved in vector format for establishment of building objects elevation by sampling at random locations.

Processed with "Create Random Points" geoprocessing tool in ArcGIS 10, the result created a feature class containing groups of points with one group for each building footprint as shown in Figure 3.5. The building heights information from the random points were then added to the building footprints and summarised with mean statistical method to generate the average roof heights (m). The building volume

(m^3) was then calculated by taking the product of the floor space (m^2) of the building footprints and the average roof heights. Visualised in ArcScene, the LiDAR-derived digital building model and building volume is shown in Figure 3.6. The colour gradient (from green to red) represents the building volume from low to very high. Using Hamaina's *et al.* (2012) method of calculation as presented earlier, the building floor space index was generated and visualised as point and stick map shown in Figure 3.7. Taken from the geometric centroid of building footprints, points from Figure 3.7 with associated building FSI were further analysed with spatial autocorrelation techniques specifically the Global Moran's I and Anselin Local Moran's I (see Section 3.3.6) to generate 5m-gridded map. The results were then reclassified to represent the building's physical vulnerability of the area (Figure 3.8). In deriving physical vulnerability attributes, an inverse relationship was assumed such that low and high values of building FSI indicate high and low vulnerability (and risk), respectively.

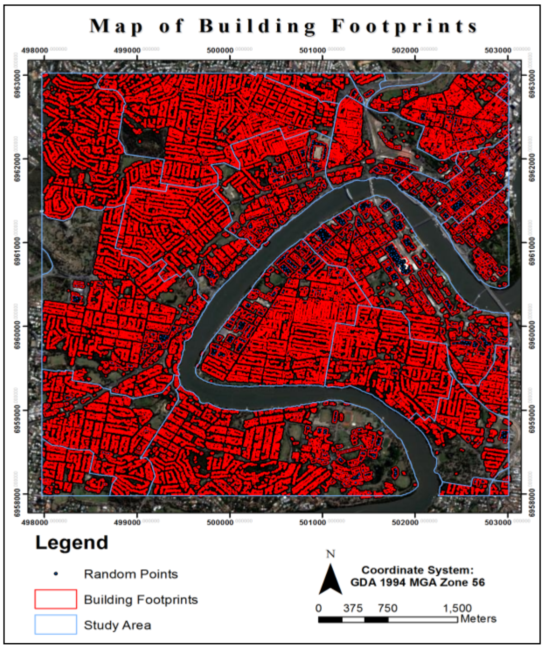


Figure 3.5 The building footprints map

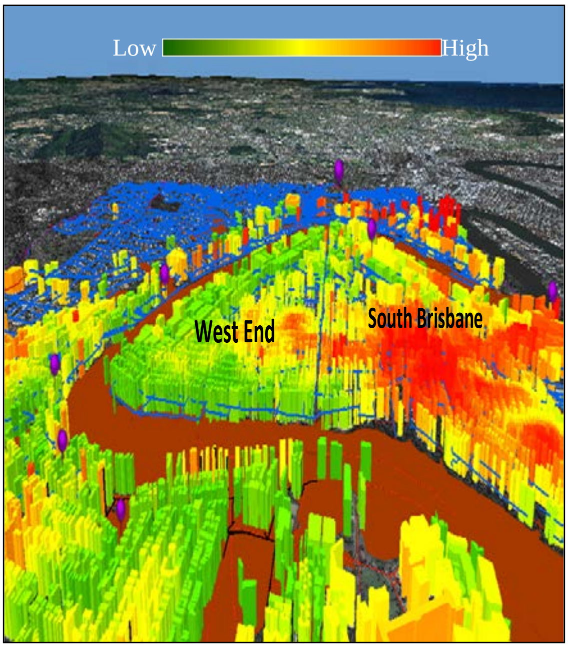


Figure 3.6 The LiDAR-derived digital building model and building volume in 3D

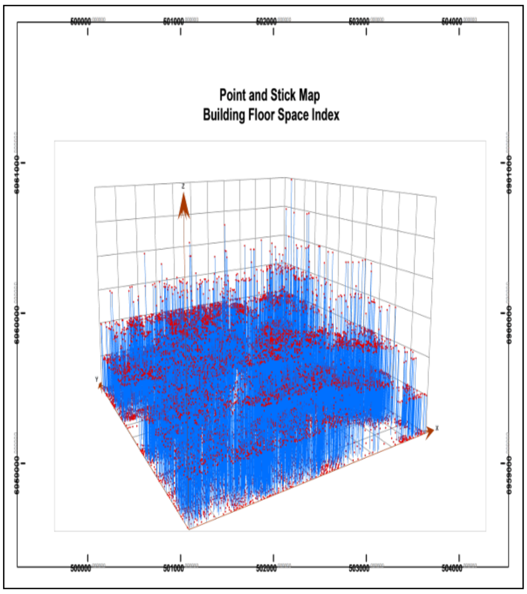


Figure 3.7 Point and stick map of building FSI

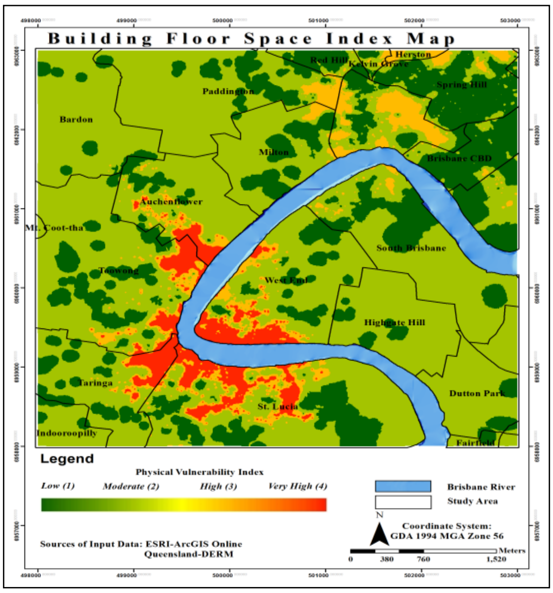


Figure 3.8 Physical vulnerability index map from building floor space

3.3.2 Spatial Analysis with Fuzzy Logic

The mathematical expression of fuzzy set theory and fuzzy logic to model ambiguity and uncertainty in decision-making is presented as follows (Akter and Simonovic 2005):

> If *X* is a collection of objects generically by *x*, then a fuzzy set *A* in *X* is a set of ordered pairs:
>
> $$A = \{x, u_A(x))|x€X\} \quad \text{Eq. 3.7}$$
>
> where $u_A(x)$ is called the membership function or grade of membership of *x* in *A*.

The membership function stated above was applied in modelling uncertainties of selected indicating variables of flood risk (i.e. hazard, physical vulnerability, social vulnerability and exposure) enumerated in Table 3.2.

This study adopted the fuzzy synthetic evaluation (FSE) method where data or values of indicating variables were divided into several categories (see Table 3.2) (Lu *et al.* 1999) according to predetermined quality criteria (i.e. lowest risk zone, lower risk zone, medium risk zone, higher risk zone, and highest risk zone) (Jiang *et al.* 2009). This study used these criteria to associate the graded interval value generated from fuzzy membership analysis. The FSE algorithm was implemented in this study by using the descending (i.e. fuzzy small) and ascending (i.e. fuzzy large) fuzzy membership functions with the geometric interpretations shown in Figures 3.8 and 3.9. These types define the fuzzy membership functions where the smaller input values or the larger input values have membership closer to 1 (ESRI 2011). From Figures 3.9 and 3.10, the blue lines represent the fuzzy values of indicating variables processed with fuzzy logic and the green, yellow, orange, and red lines represent the crisp sets after having the fuzzy values "defussified" using the fuzzy synthetic evaluation technique.

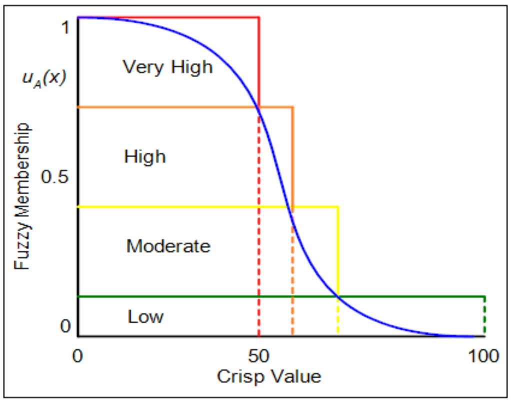


Figure 3.9 The geometric interpretation of fuzzy small membership

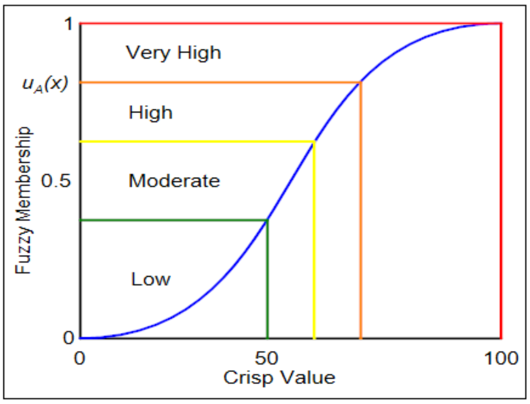


Figure 3.10 The geometric interpretation of fuzzy large membership

Utilising the fuzzy membership tool of Spatial Analyst in ArcGIS 10, the fuzzy membership values (FMV) of selected indicating variables of hazard, social vulnerability, and exposure were obtained through the process called fuzzification following the Hinkel's (2011) linear and monotonous operation of indicating variables and explicit assumptions specified in Table 3.1. Fuzzification is the process of converting attributes into a homogenous scale by assigning memberships with respect to predefined fuzzy subsets (Sadiq *et al.* 2004). As users being required to provide the midpoint or centroid of crisp value (except for flood hazard as discussed earlier), the value was obtained by averaging the minimum and the maximum values of an indicating variable.

As FSE method eliminates the possible fuzziness (Jiang *et al.* 2009), the fuzzy membership values ($u_A(x)$) of the indicating variables used in the analysis were defuzzified into four classes according to perceived level of flood risk (PFR): low risk, moderate risk, high risk and very high risk. Defuzzification is a process in FSE that calculates the crisp value (i.e. grade interval) of a fuzzy set (Sadiq *et al.* 2004). The grade interval values for this study were obtained through geometric interval classification of the raster data fuzzy set. As a compromise method between equal interval and quantile (ESRI 2010), geometric intervals were used to delineate classes based on natural groupings of fuzzy membership values. This option tries to find a balance between highlighting the changes in the middle values and the extreme values (ESRI 2011). Using this argument, FMV ($u_A(x)$) can be expressed in the following mathematical equations (Zadeh 1975):

$$u_A(x) = \int \frac{uF(u)}{u} \qquad \text{Eq. 3.8}$$

where: uF: → [0, 1] is the membership; and integral denotes the union of fuzzy singletons $uF(u)/u$ over the universe of discourse (i.e. universe of an indicating variable) denoted by U such that the fuzzy subset of U would be expressed as:

$$(u_A(x) = \int_0^1 \frac{1}{1+u^2} /2 \qquad \text{Eq. 3.9}$$

which means that $(u_A(x)$ is a fuzzy subset of the unit interval [0, 1] whose membership function is defined by

$$uF(u) = \frac{1}{1+u^2} \qquad \text{Eq. 3.10}$$

Using the four geometric interval classes (low risk, moderate risk, high risk, and very high risk), the membership function of the fuzzy subset was expressed as (Zadeh 1975):

s(u: α, β, γ)	= low risk (0)	for $u \leq \alpha$	Eq. 3.11
	= moderate risk $(2\ \frac{u-\alpha^2}{\gamma-\alpha})$	for $\alpha \leq u \leq \beta$	
	= high risk $(1-2\ \frac{u-\alpha^2}{\gamma-\alpha})$	for $\beta \leq u \leq \gamma$	
	= very high risk (1)	for $u \geq \gamma$	

where the parameter $\beta = \frac{\alpha+\gamma}{2}$ is the crossover point.

The following figures (Figures 3.11-3.13) show the processed maps using GIS-based fuzzy synthetic evaluation technique. Each figure depicts the vulnerability (and risk) index of the study area using the classified FMVs of indicating variables as summarised in Appendix 1.

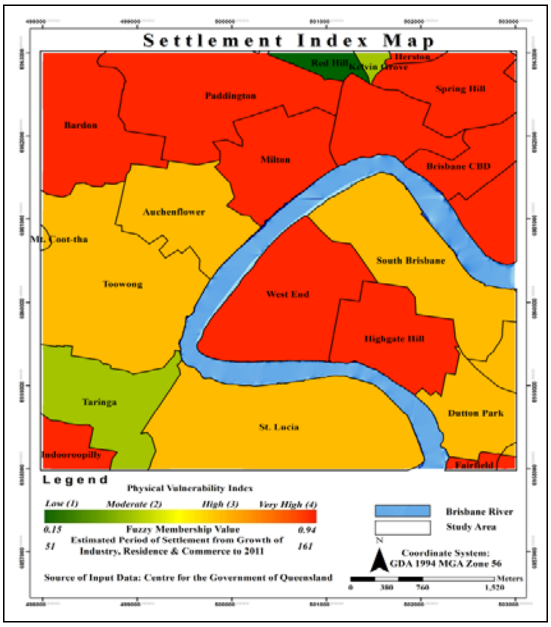


Figure 3.11 The physical vulnerability index map of settlement indicating variable processed with fuzzy logic

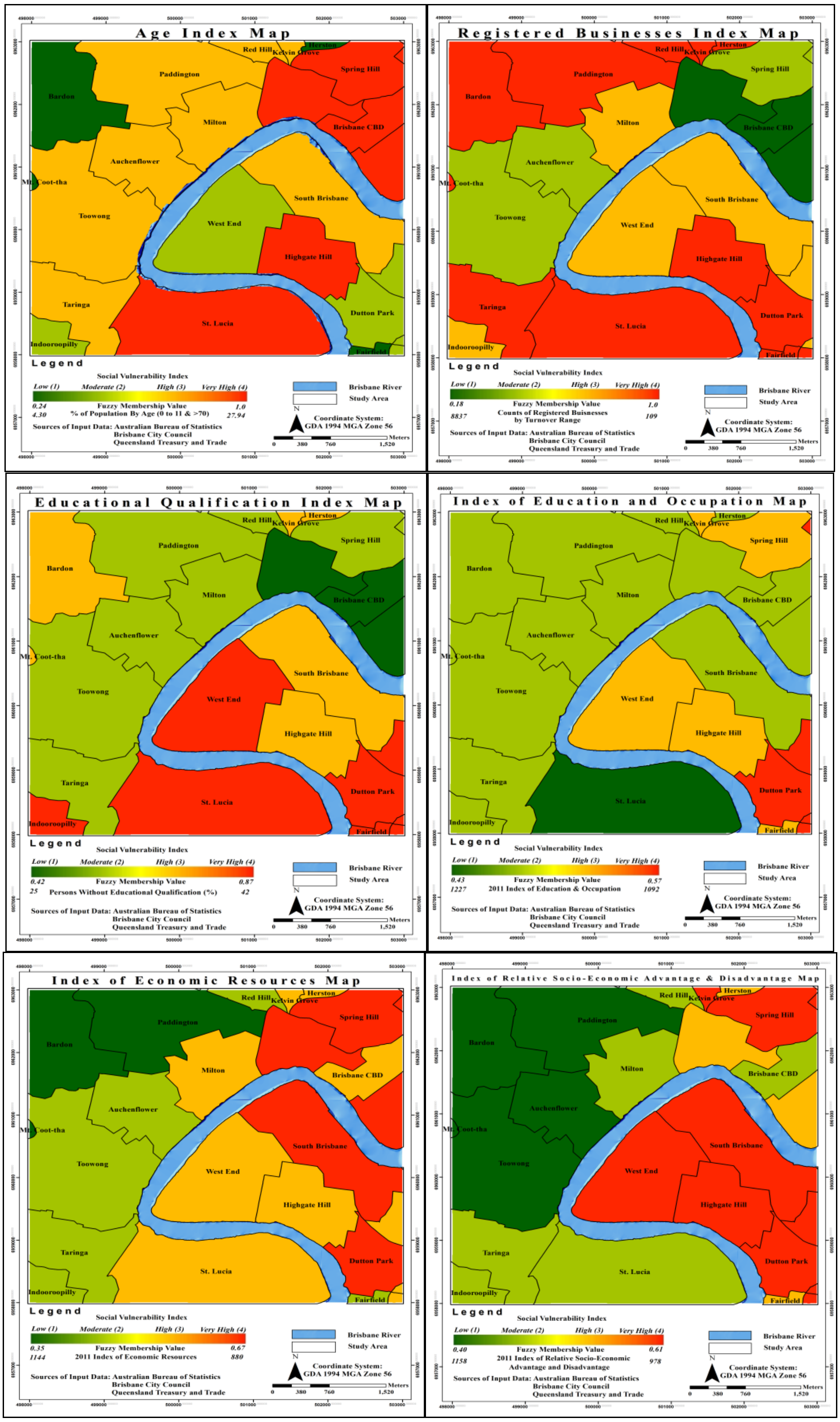


Figure 3.12 Index maps of fifteen (15) social vulnerability indicating variables processed with fuzzy logic (*continued next page)*

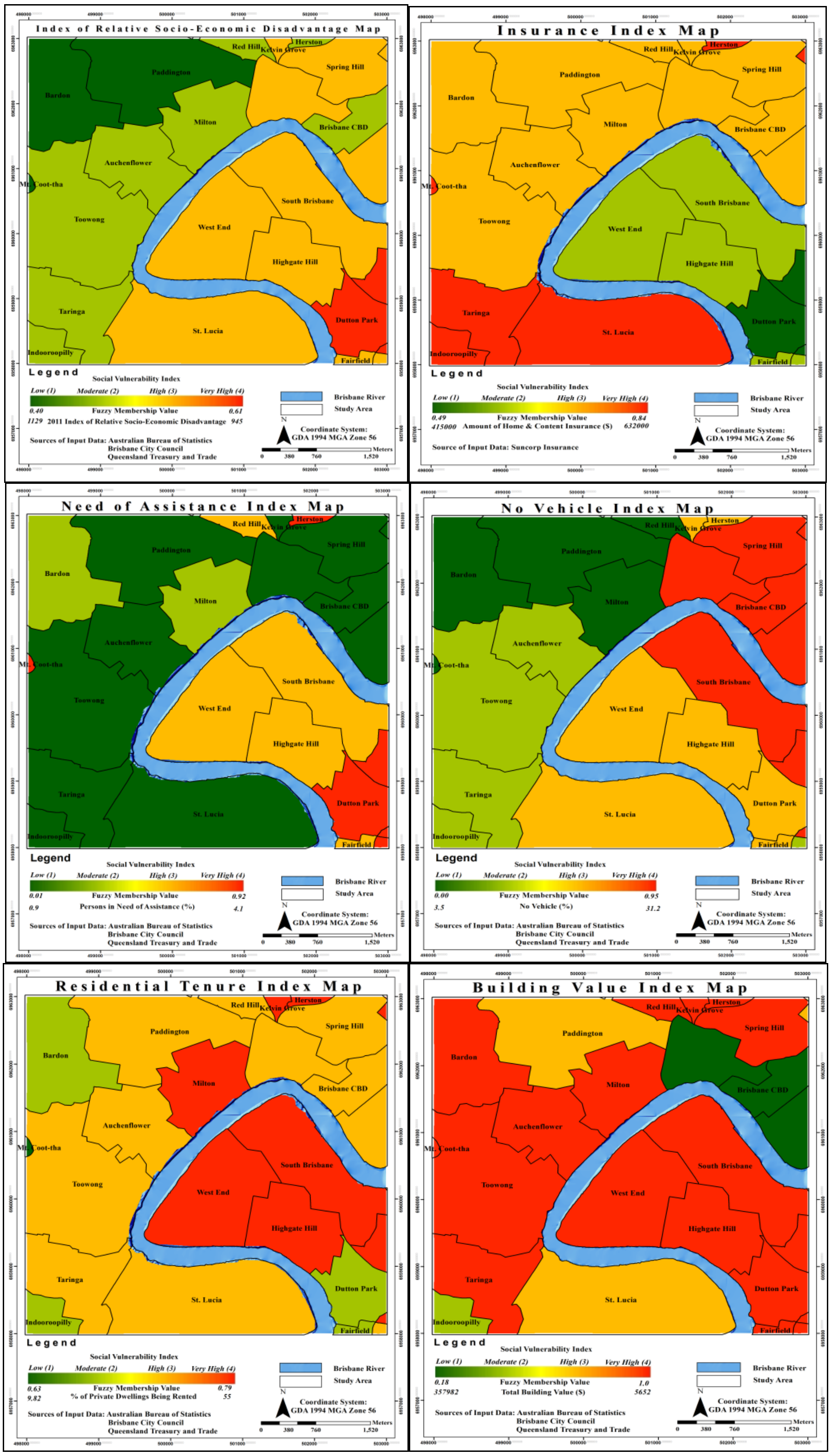


Figure 3.12 Index maps of fifteen (15) social vulnerability indicating variables processed with fuzzy logic (*continued from previous page*)

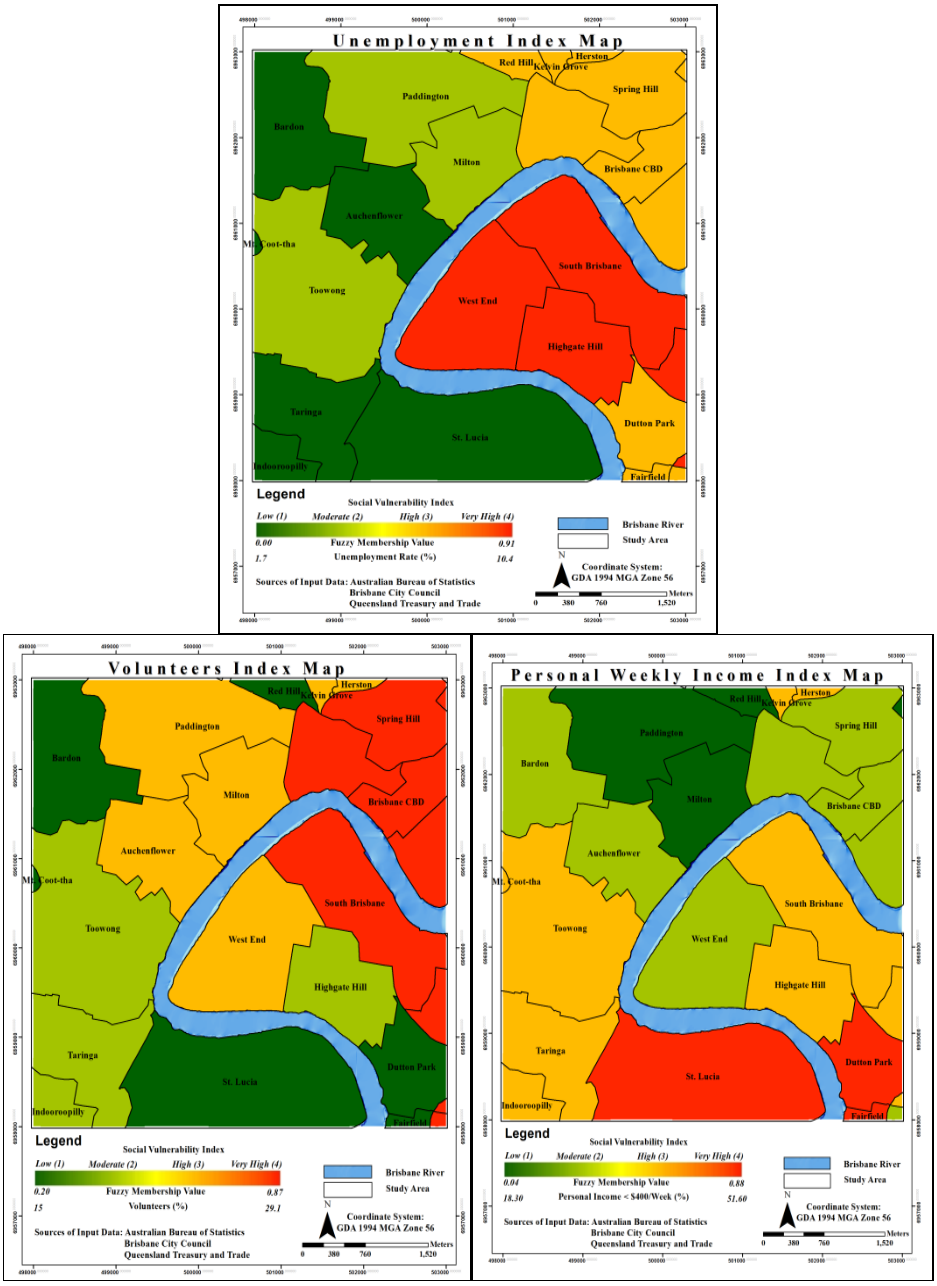


Figure 3.12 Index maps of fifteen (15) social vulnerability indicating variables processed with fuzzy logic (*continued from previous page*)

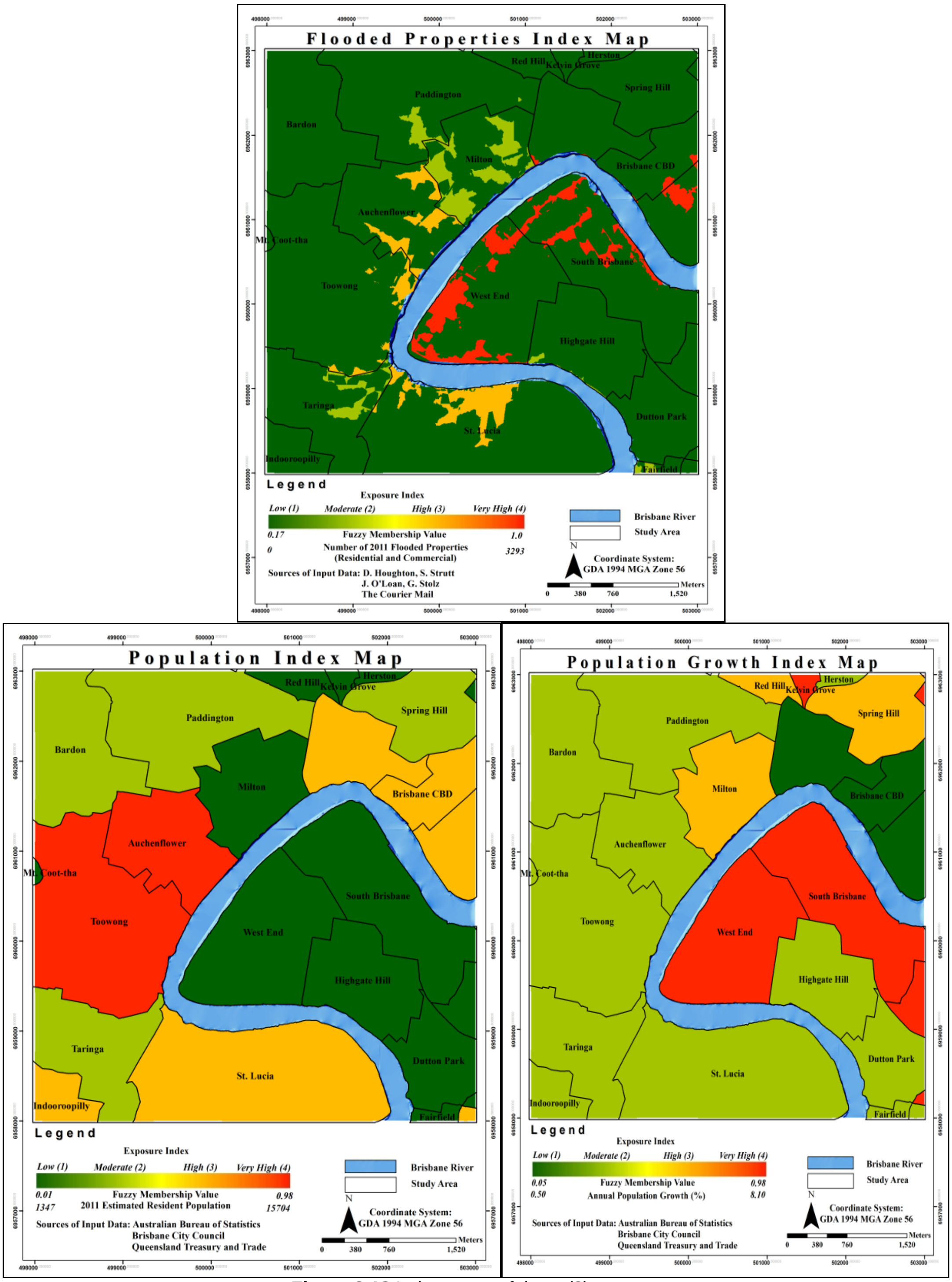


Figure 3.13 Index maps of three (3) exposure indicating variables processed with fuzzy logic

3.3.3 Proximity Analysis

Another important spatial quantification technique used in this study is the proximity analysis. This is a type of analysis in which geographic features (points, lines, polygons or raster cells) are selected based on their distance from other features or cells (Wade and Sommer 2006).

In this study, the vector-based proximity measurements using two input features: the distance (*D*) between two points p_1 and p_2 and the centre of gravity or centroid of a polygon (x_c, y_c) were applied in determining access to emergency services and emergency response time. The D (p_1, p_2) was calculated using the Pythagorean Theorem and x_c, y_c were estimated by means of the following equations (Lo and Yeung 2007):

$$D\left(p_{1,}p_2\right) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \qquad \text{Eq. 3.12}$$

$$x_c = \frac{1}{6A}\sum_{i=1}^{n}(x_i + x_{i+1})\,(x_i y_i + x_{i+1} - y_i x_{i+1}) \qquad \text{Eq. 3.13}$$

$$y_c = \frac{1}{6A}\sum_{i=1}^{n}(y_i + y_{i+1})\,(x_i y_i + x_{i+1} - y_i x_{i+1}) \qquad \text{Eq. 3.14}$$

where p_1 is being represented by locations of emergency and p_2 is the centroid of building footprints.

Fifty four (54) emergency services (i.e. police stations including beat shopfronts, fire and rescue stations, hospitals and medical centres, and January 2011 flood evacuation centre) were included in the analysis. These points were digitised from Google Earth, saved in KML format, and then exported into shapefile format. Using the point distance tool in ArcGIS 10, the outcome created a table of the calculated average distances between emergency services and buildings. The results then were used to calculate the emergency response time (ERT). Emergency response time was considered in this study as the ability of emergency crews to respond in an emergency situation (e.g. flood) for a given time that travelled 30kph speed drive. It was assumed in this paper that emergency crews could not travel or drive at a higher speed due to fallen trees and electricity transmission lines along the roads with delayed time from rerouting; hence, a reduction in driving speed and consequently a non-straightforward emergency response.

Through this exercise, the concept of proximity was extended from physical measurement distance to the calculation of movement times and other impedance factors such as weather conditions, presence of water bodies, traffic density and speed, and other barriers (Lo and Yeung 2007). As specified earlier, the 30kph driving speed and fallen trees and electricity transmission lines were assumed as potential impedance factors and barriers.

The results of proximity analyses were then further analysed with spatial autocorrelation techniques to cluster the point representations of emergency services. The derived values were then interpolated with inverse distance weight (IDW) method to represent perceived level of risks based on access to and response time from emergency services. Longer distances and travel times between emergency services and buildings indicate very highly vulnerable areas as shown in Figure 3.14.

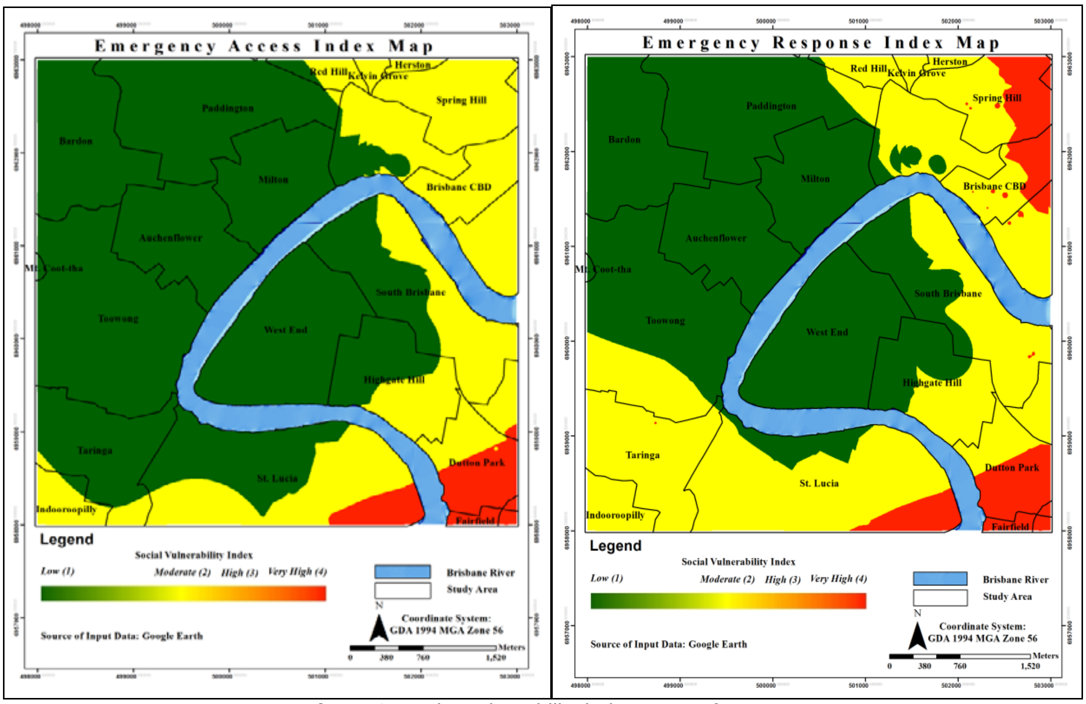


Figure 3.14 The vulnerability index maps of access to emergency services and response time

3.3.4 Quadrat Analysis

The specific use of quadrat analysis in this study dealt with the detection of point patterns of infrastructure connections/services and culturally significant assets (i.e. heritage sites). Infrastructure connection is defined in this study as the physical contact point between infrastructure service providers and consumers. Operationally, this definition involved the identification of the locations of nodes in the infrastructure network topology wherein the infrastructure service concludes and consumer starts to access the service.

Using the quadrat counting method (QCM), this study analysed the spatial patterns of the infrastructure nodes and heritage sites to assess the number of consumers or end-users and cultural assets that were exposed to the January 2011 flood event. The QCM consists of partitioning the area into Q subsets (or quadrats) (Miranda *et al.* 2011) through the following equation (Wong and Lee 2005):

$$Q_s = 2A/r \qquad \text{Eq. 3.15}$$

where:

Q_s is the quadrat size
A area of the study area

r is the number of infrastructure nodes/points (i.e. electricity, sewerage, stormwater, water supply, and heritage sites)

In generating the Q subsets, a fishnet was created in ArcGIS 10 and spatially joined the infrastructures nodes with the intersect tool into the fishnet to count its number per Q subset. The infrastructures nodes evaluated in this study are listed in Table 3.5. Through this method, this study enabled to evaluate the distribution of point locations of infrastructure connections/services distribution by examining the density (expressed as the number of connections or heritage sites per quadrat) changes over space (Wong and Lee 2005). The infrastructure node density and heritage site density were further analysed with spatial autocorrelation techniques and hot spot analysis, respectively, to detect their level of spatial autocorrelation and associated perceived level of exposure (and risk) to flood hazard. The red areas in Figure 3.15 indicate very high exposure of consumers/end-users of critical infrastructure services to flood hazard; hence, designated with very high risk classification. Exposure map of heritage sites are discussed under a separate section intended for hot spot analysis (see Section 3.3.7).

Table 3.5 The infrastructure nodes/points used in quadrat analysis for exposure assessment

Infrastructure Asset	Infrastructure Node/Point (r)
Electricity	Electricity pole sites
Sewerage	Reticulation inlets
Stormwater	Stormwater end structures/pipe outlets
Water Supply	Water service pipe outlets
Heritage Sites	Polygon centroids of heritage sites based on land use map

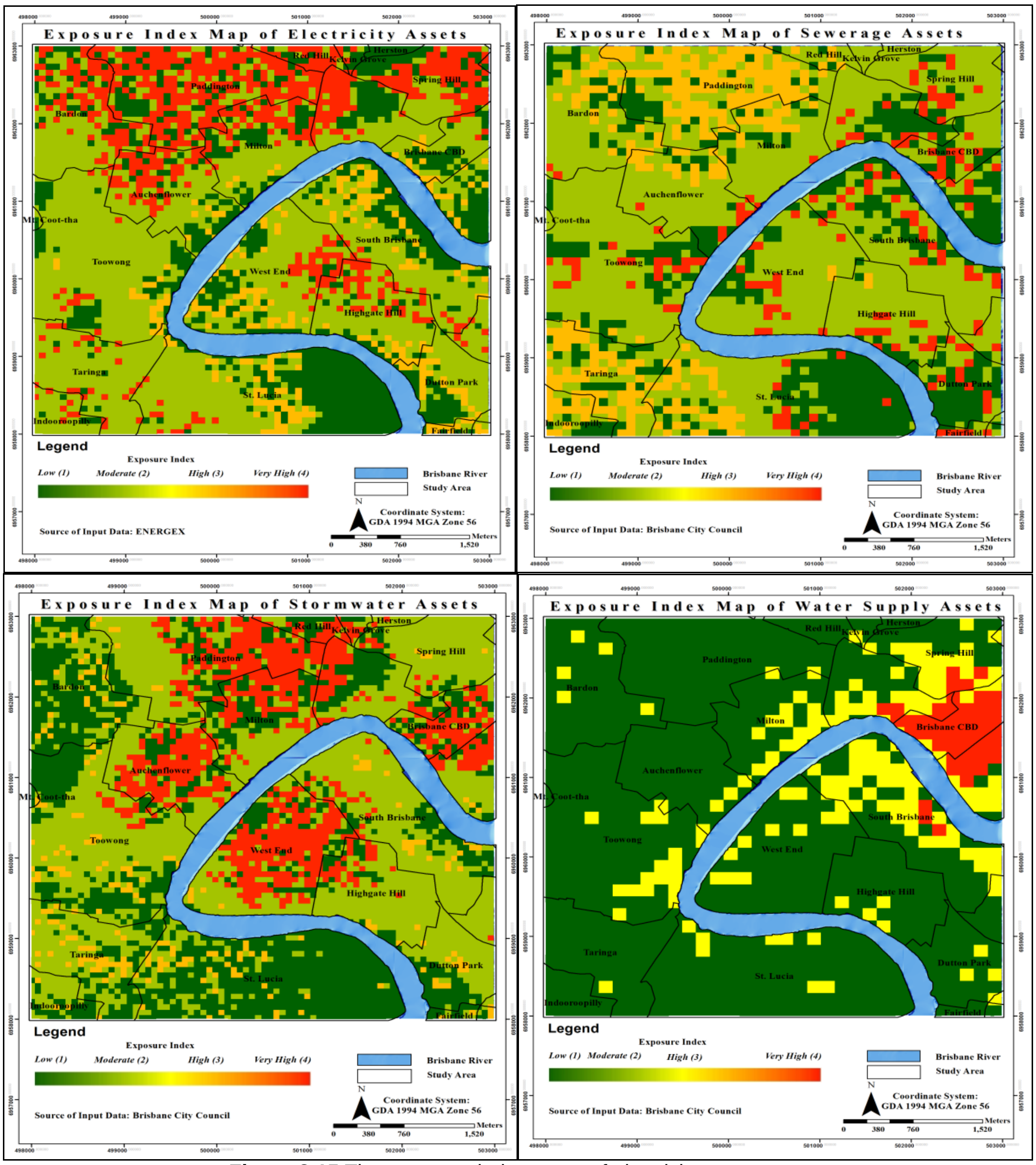


Figure 3.15 The exposure index maps of electricity, sewerage, stormwater, and water supply assets

3.3.5 Spatial Statistics with Collect Events Analysis

As available analytical tool in ArcGIS 10, collect events analysis was found appropriately applicable to hazard point features gathered by the Queensland Fire and Rescue Service (QFRS) during the rapid damage assessment following the January 2011 flood event. Through this tool, point locations of biological, chemical, electricity, and building damage hazards within flood extent were converted into weighted point features. This was found applicable to these data because of insufficient number of incidents or observations before spatial autocorrelation techniques can be successfully executed. For this type of data, weighted points were required rather than individual incidents (ESRI 2011). In effect, this analytical tool combined coincident points representing these consequential hazards and produced single “ICOUNT” field in the attribute table holding the sum of all hazard incidents for each unique location.

The results of the analysis were further analysed with spatial autocorrelation techniques to cluster the weighted hazard points and interpolated with inverse distance weight (IDW) technique to generate perceived flood risk maps. As a result of January 2011 flood, the maps shown in Figure 3.16 are the generated consequential hazard maps. The red areas in the map (very high classification) signify areas with high counts of hazard points; hence, indicated as highly hazardous areas.

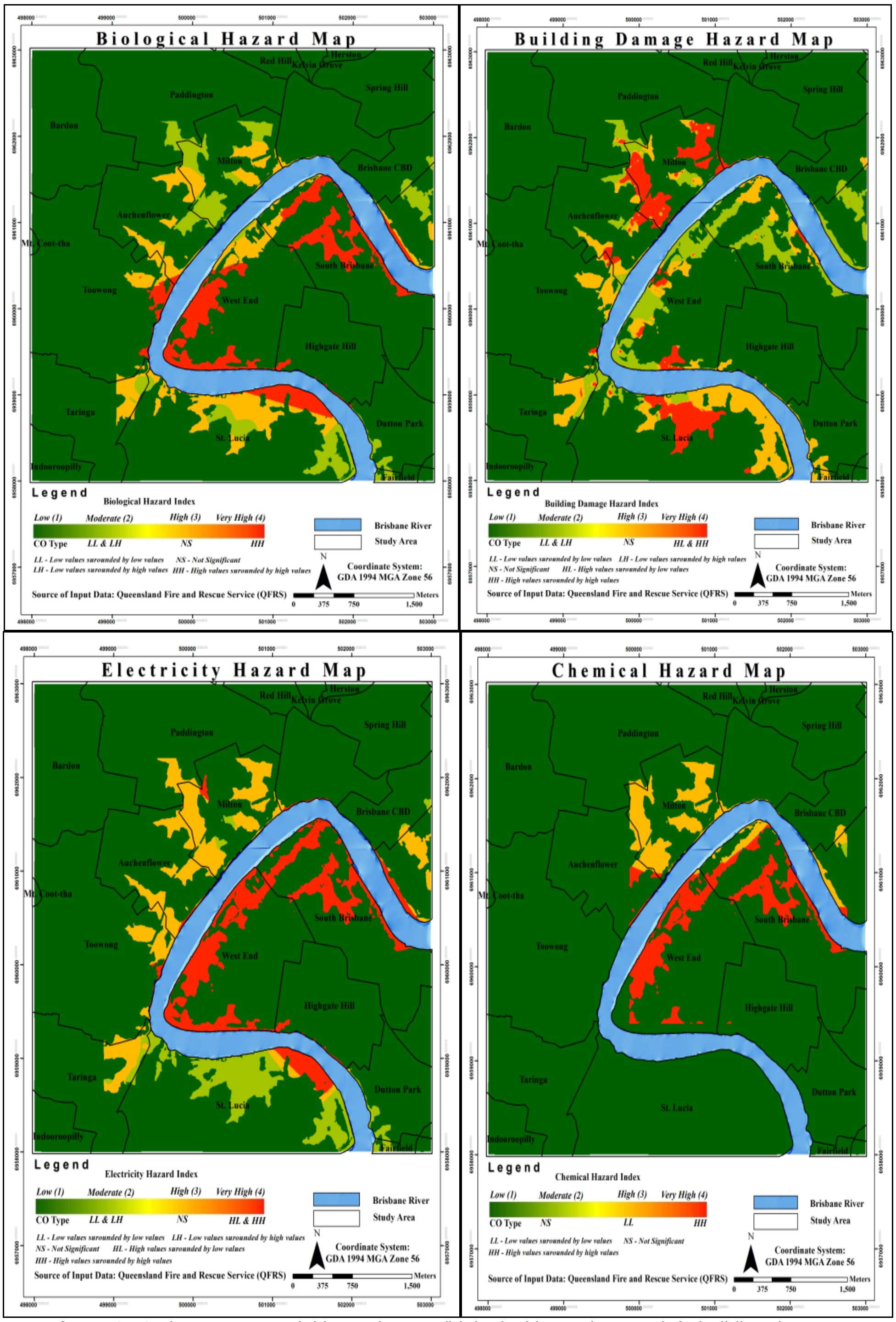


Figure 3.16 The consequential hazard maps (biological hazard, upper left; building damage, upper right; electricity hazard, lower left; and chemical hazard, lower right) of the study area

3.3.6 Modelling with Spatial Autocorrelation

Noticeably from previous discussions, spatial autocorrelation techniques played a significant role in the process of standardisation to some datasets. This section is provided to explain how this study operationalised the concept of spatial autocorrelation techniques.

The magnitude of spatial autocorrelation or spatial association of geographic events can be measured in a global or local scale. The global measures of spatial autocorrelation describe the overall spatial relationship; while, local measures of spatial autocorrelation describe the regional variability of spatial relationship of the study area (Wong and Lee 2005). For this study, both measures of spatial autocorrelation were applied. Specifically, the global measure regarded in this study was Moran's I and the local measure was the Anselin Local Moran's I with equations shown as follows (Wong and Lee 2005; ESRI 2011):

$$I = \frac{n\sum_i^n * \sum_j^n Wij(Xi - \overline{X})(Xj - \overline{X})}{W\Sigma(Xi - \overline{X})^2} \quad \text{Eq. 3.16}$$

$$E_I = \frac{-1}{n-1} \quad \text{Eq. 3.17}$$

$$Z_I = \frac{I - E_I}{\sqrt{VI}} \quad \text{Eq. 3.18}$$

$$VI = E(I^2) - E(I)^2 \quad \text{Eq. 3.19}$$

where:

I is the global Moran's I index of an indicating variable
X_i is the derived field value for each dataset
w is the sum of all elements of the spatial weights matrix
E_I is expected value for global Moran's I
Z_I is the critical z-score for global Moran's I.
VI is the statistical variance for global Moran's I.

$$I_i = z_i \sum_j w_{ij} z_j \quad \text{Eq. 3.20}$$

$$E[I_i] = \frac{-w_i}{n-1} \quad \text{Eq. 3.21}$$

$$z\,[I_i] = \frac{I_i - E[I_i]}{\sqrt{Var\,[I_i]}} \quad \text{Eq. 3.22}$$

where:

I_i is the local Moran's I index of an indicating variable
z_i and z_j are deviations from the mean for the corresponding x values
$E[I_i]$ is the expected value of randomness for local Moran's I
$Z[I_i]$ is the critical z-score for local Moran's I
Var is the statistical variance for local Moran's I.

As inferential statistics, the results of the global and local measures of spatial autocorrelation analyses were interpreted within the context of a null hypothesis. This study hypothesised that the observed patterns of indicating variables (see Table 3.2) were spatially random at 95% level of confidence.

The calculated values were then interpreted whether the statistics indicate a strong positive autocorrelation or strong negative autocorrelation. An extremely negative autocorrelation was indicated by -1 Moran's I index while an extremely positive autocorrelation was indicated by +1 Moran's I index. The expected value for Moran's I (E_I) were then compared with the observed Moran's I index (I) as another way of interpreting the spatial autocorrelation. There was no spatial autocorrelation when the observed negative Moran's I was larger than the negative expected value (Wong and Lee 2005). When the critical z-score was between -1.96 and +1.96 associated with 0.05 p-value larger than 0.05, the pattern exhibited was a result of a random spatial process; hence, the decision rule was to accept the null hypothesis. The calculated global Moran's I statistics of flood risk and climate adaptation capacity indicating variables are presented in Appendix 2.

To assess the reliability of the critical z-scores, distances with interval of 100 were preselected and iteratively used in the calculation of observed Moran's I, expected value for Moran's I, and z-score until the z-score reached zero or close to zero. The distance bands and z-score values were then graphed against each other in MATLAB to determine the peak values from the function curves as shown in Figures 3.17-3.20. As perceived to be tangential to the function curves, these generated peak points (in red dots) provided the z-score with corresponding distance band for each indicating variable (see Table 3.6) which in turn used in calculating the cluster and outlier (i.e Anselin Local Moran's I) statistics.

The main limitation of the Global Moran's I observed in this study, however, was that it did not account the variability of features distribution across the study region. Hence, it was reasonable to examine the magnitude of spatial autocorrelation whether the distribution of observed events is variable. The Anselin Local Moran's I was tested to investigate the possibility of finding positive spatial autocorrelation in one part of the region or negative spatial autocorrelation in another part of the region.

Table 3.6 Summary of generated z-scores and distance bands of food risk and climate adaptation capacity indicating variables used in the local Moran's I

Component	Indicating Variable	Z-score	Distance Band (m)
Hazard	Biological	21	1900
	Building Damage	143	240
	Chemical	28	1100
	Electricity	102	502
Physical Vulnerability	Building FSI	78	2600
	Electricity Infrastructure	68	650
	Sewerage Infrastructure	29	900
	Stormwater Infrastructure	48	400
	Water Supply Infrastructure	236	1000
Social Vulnerability	Access to Emergency Services	16	3092
	Emergency Response Time	16	3092
Exposure	Electricity Infrastructure	85	600
	Heritage Sites	13	2000
	Sewerage Infrastructure	49	950
	Stormwater Infrastructure	130	700
	Water Supply Infrastructure	83	900

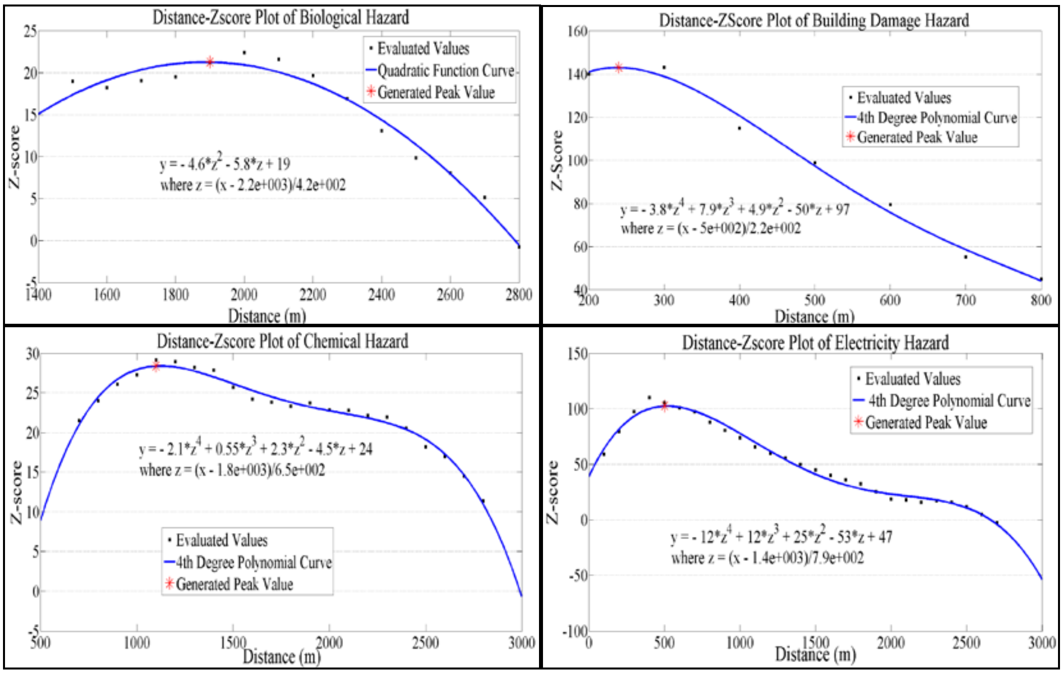


Figure 3.17 The function curves of hazard indicating variables (quadratic function curve of biological hazard, upper left; 4th degree polynomial curves of building damage, upper right; chemical hazard, lower left; and electricity hazard, lower right)

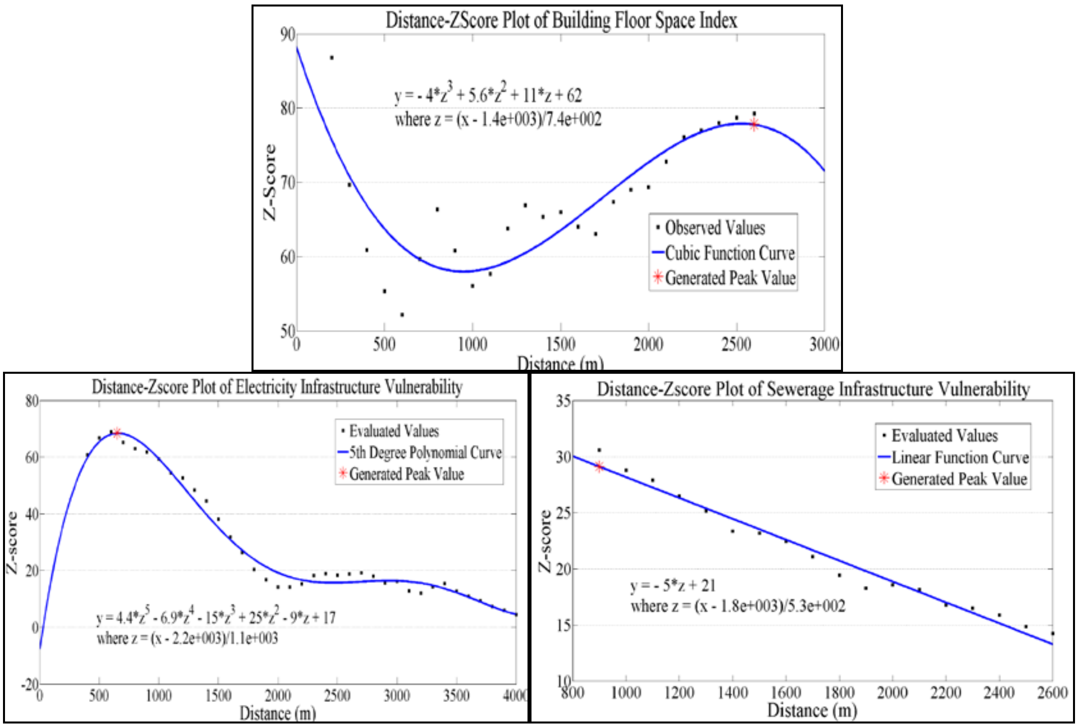


Figure 3.18 The function curves of physical vulnerability indicating variables (cubic function curve of building FSI, top; 5th degree polynomial curve of electricity, bottom left; and linear function curve of sewerage, bottom right) (*continued next page*)

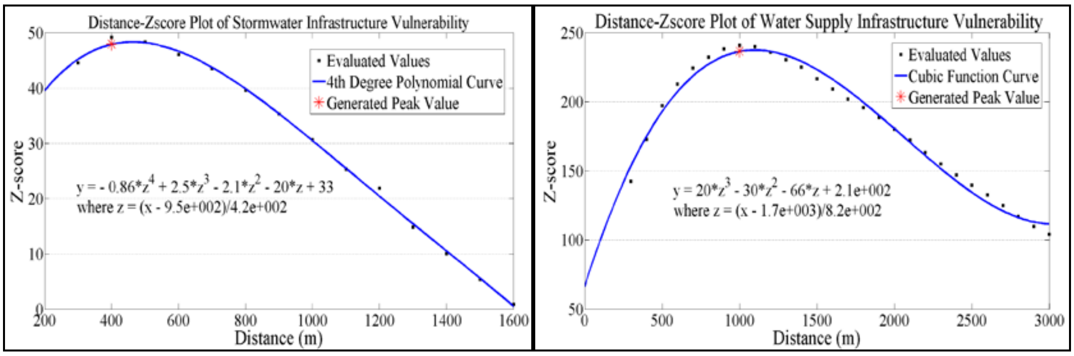


Figure 3.18 The function curves of physical vulnerability indicating variables (4th degree polynomial curve of stormwater, left; and cubic function curve of water supply , right) (*continued from previous page*)

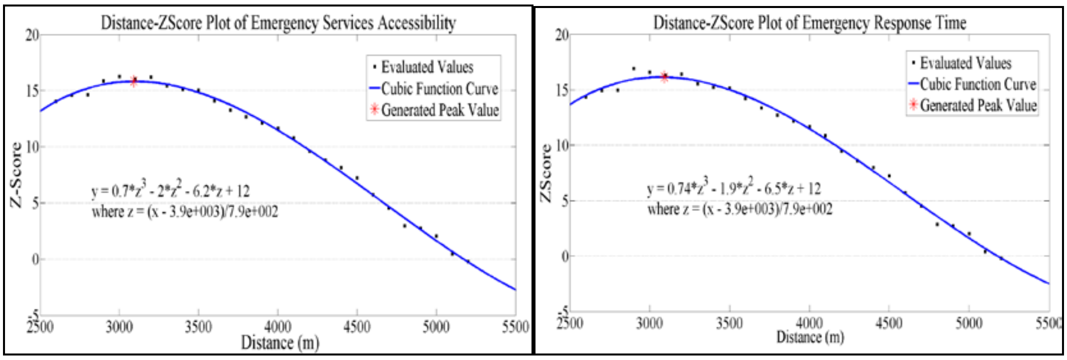


Figure 3.19 The function curves of social vulnerability indicating variables (cubic function curves of access to emergency services, left; and emergency response time, right)

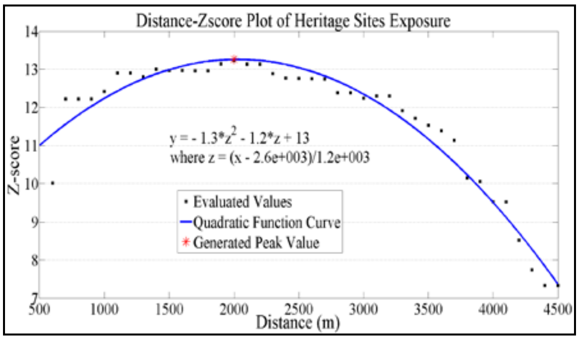


Figure 3.20 The function curves of infrastructures' exposure indicating variables (*continued next page*)

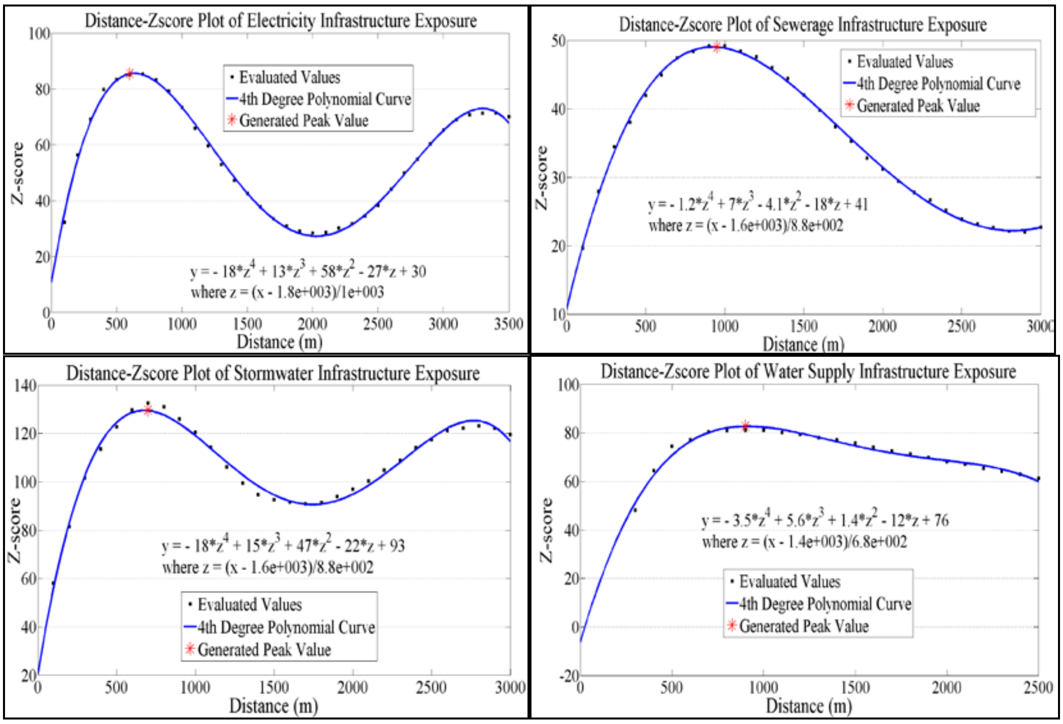


Figure 3.20 The function curves of infrastructures' exposure indicating variables (quadratic function curve of heritage sites, top; 4th degree polynomial curves of electricity, upper left; sewerage, upper right; stomrwater, lower left; and water supply, lower right) *(continued from previous page)*

The local clustering or dispersion of geographic features was then analysed based on statistical values. A positive value for I_i indicates a positive correlation because the feature is surrounded by features with similar values; hence, the feature is part of a cluster (Wong and Lee 2005; ESRI 2011). A negative value for *Ii* indicates a negative autocorrelation because the feature is surrounded by features with dissimilar values; hence, an outlier (Wong and Lee 2005; ESRI 2011). As a relative measure of spatial autocorrelation, local Moran's I is best interpreted within the context of critical z-scores. When the calculated z-scores at 95% level of confidence were between -1.96 and +1.96, the null hypothesis was accepted. The spatial distribution of the geographic features on this regard has exhibited a random pattern.

When cluster and outlier (CO) analysis was performed in ArcGIS 10, CO Type was identified as the best indication of representing cluster and outlier being not a relative measure of spatial autocorrelation and set apart the clusters from outliers using the 95% level of statistical confidence.

However, using CO Type was found to have its own limitation. Performing interpolation with a nominal scale of measurement is completely impossible in GIS. The remedy then was to assign ordinal values (AOV) according to degree of spatial clustering of examined indicating variables and its associated level to perceived flood risk. Extra care was observed in assigning these values and performing interpolation to maintain the associated statistical significance. Tables 3.7-3.10 show the CO Type classes from selected indicating variables with assigned ordinal values (AOV) and perceived levels of flood risk (PFR).

Those tables were generated based on the assumed relationship of indicating variables with the perceived level of flood risk (PFR). For example, the assigned values for emergency access and response and electricity hazard were observed to have correlated with CO type such that assigned value of 1 indicates an LL classification and 4 with an HH classification. This means that low attributes surrounded by low attributes (LL) indicated a low level of perceived flood risk while high attributes surrounded by high attributes (HH) indicated a high level of perceived flood risk. For building FSI, an inverse relationship was observed in associating the level of perceived flood risk (PFR). The assigned value of 1 to LL CO type means that a low building floor space index value surrounded by low floor space index values (LL) indicated that the building was highly physically vulnerable to flood risk; hence the assigned value for PFR was 4. The assigned ordinal values and perceived levels of flood risk of other indicating variables followed this rule of inference (see Tables 3.7-3.10).

After having identified the CO type classes of indicating variables and assigned ordinal values with corresponding levels of flood risk, interpolation was done using the Inverse Distance Weight (IDW) method. This technique interpolated the raster surface from points using an inverse distance weight.

The Inverse Distance Weight (IDW) method of interpolation also adopts the Tobler's First Law of Geography. This method assumes that the variable being mapped decreases influence with distance from the sampled location (ESRI 2011). The inverse of the distance is controlled by the power parameter as the weight such that higher power values can emphasise nearest points (ESRI 2011). This method was operationalised in ArcGIS 10 based on the following equation (Watson and Philip 1985):

$$P_i = \frac{\sum_{j=1}^{G} P_j / D_{ij}^n}{\sum_{j=1}^{G} \frac{1}{D_{ij}^n}} \qquad \text{Eq. 3.23}$$

where

P_i is the property at location i
P_j is the property at sampled location j
D_{ij} is the distance from i to j
G is the number of sampled location
n is the inverse-distance weighting power

Table 3.7 The CO Type classes of hazard indicating variables with assigned ordinal values and perceived levels of flood risk

CO Type	Biological		Building Damage		Chemical		Electricity	
	AOV	PFR	AOV	PFR	AOV	PFR	AOV	PFR
LL	1	1	1	1	3	3	1	1
HL	-	-	3	3	-	-	3	3
LH	2	2	1	1	-	-	2	2
HH	4	4	3	3	4	4	4	4
NS	3	3	2	2	2	2	2	2

LL – Low values surrounded by low values; HL – High values surrounded by low values; LH – Low values surrounded by high values; HH – High values surrounded by high values; NS – Not significant; AOV – Assigned ordinal values; PFR – Perceived flood risk with 1 being low, 2 moderate, 3 high, and 4 very high.

Table 3.8 The CO Type classes of physical vulnerability indicating variables with assigned ordinal values and perceived levels of flood risk

CO Type	Building FSI		Electricity		Sewerage		Stormwater		Water Supply	
	AOV	PFR	AOV	PFR	AOV	PFR	AOV	PFR	AOV	PFR
LL	1	4	1	4	2	2	-	-	1	4
HL	4	1	4	1	3	3	2	3	3	2
LH	2	3	2	3	2	2	2	2	-	-
HH	4	1	4	1	4	4	3	4	4	1
NS	3	2	3	2	1	1	1	1	2	3

LL – Low values surrounded by low values; HL – High values surrounded by low values; LH – Low values surrounded by high values; HH – High values surrounded by high values; NS – Not significant; AOV – Assigned ordinal values; PFR – Perceived flood risk with 1 being low, 2 moderate, 3 high, and 4 very high.

Table 3.9 The CO Type classes of social vulnerability indicating variables with assigned ordinal values and perceived levels of flood risk

CO Type	Emergency Access		Emergency RT	
	AOV	PFR	AOV	PFR
LL	1	1	1	1
HL	-	-	-	-
LH	-	-	-	-
HH	3	3	3	3
NS	2	2	2	2

LL – Low values surrounded by low values; HL – High values surrounded by low values; LH – Low values surrounded by high values; HH – High values surrounded by high values; NS – Not significant; AOV – Assigned ordinal values; PFR – Perceived flood risk with 1 being low, 2 moderate, 3 high, and 4 very high.

Table 3.10 The CO Type classes of exposure indicating variables with assigned ordinal values and perceived levels of flood risk

CO Type	Electricity		Sewerage		Stormwater		Water Supply	
	AOV	PFR	AOV	PFR	AOV	PFR	AOV	PFR
LL	1	1	1	1	1	1	1	1
HL	3	3	4	4	3	3	3	3
LH	1	1	1	1	1	1	3	3
HH	4	4	3	3	4	4	4	4
NS	2	2	2	2	2	2	1	1

LL – Low values surrounded by low values; HL – High values surrounded by low values; LH – Low values surrounded by high values; HH – High values surrounded by high values; NS – Not significant; AOV – Assigned ordinal values; PFR – Perceived flood risk with 1 being low, 2 moderate, 3 high, and 4 very high.

Figures 3.21-3.24 show the cluster and outlier maps (foreground) and perceived level of risk maps (background) generated from spatial autocorrelation techniques and IDW technique, respectively.

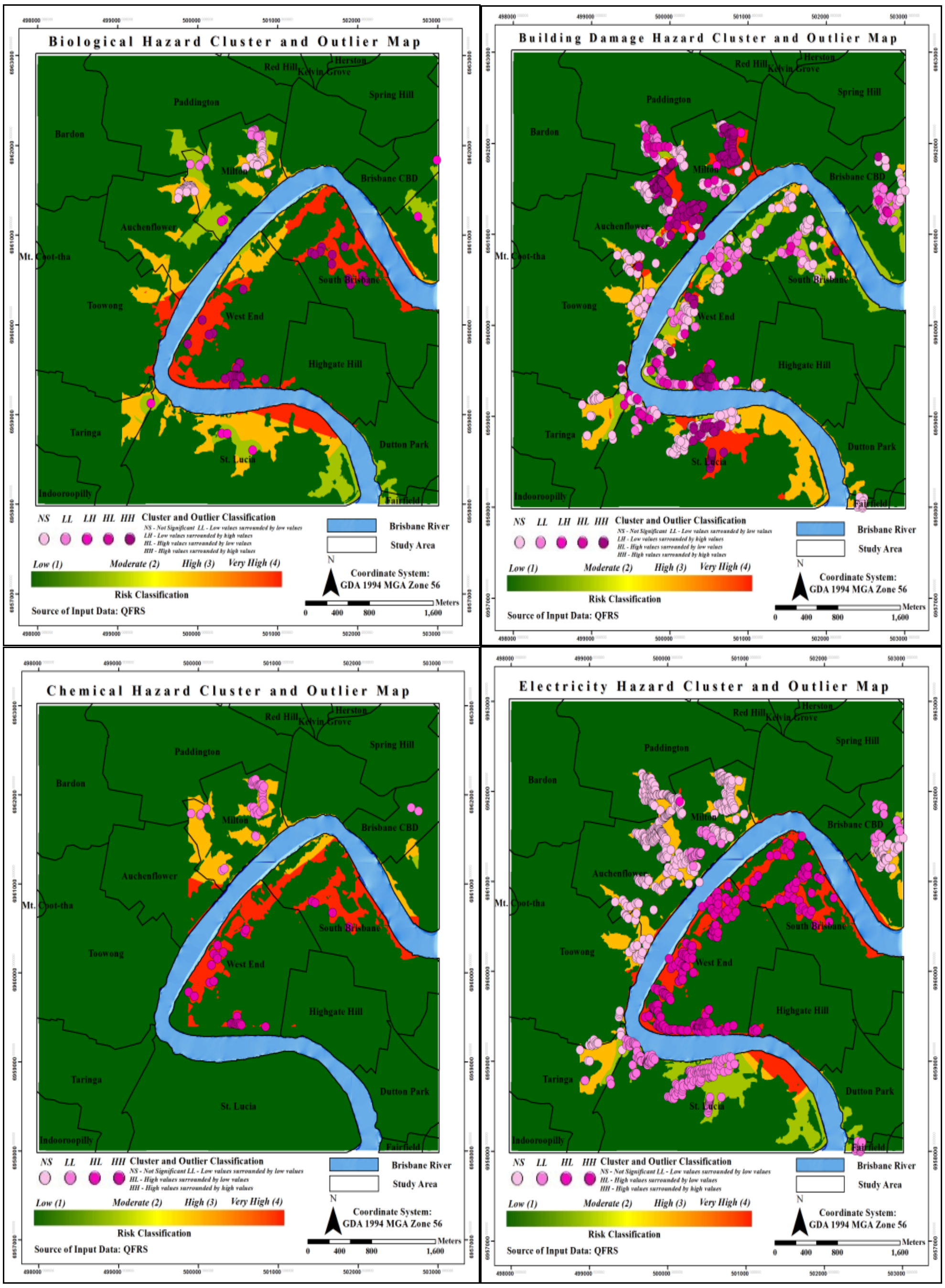


Figure 3.21 The cluster and outlier (CO) maps of hazard indicating variables (biological hazard, upper left; building damage, upper right; chemical hazard, lower left; and electricity hazard, lower right)

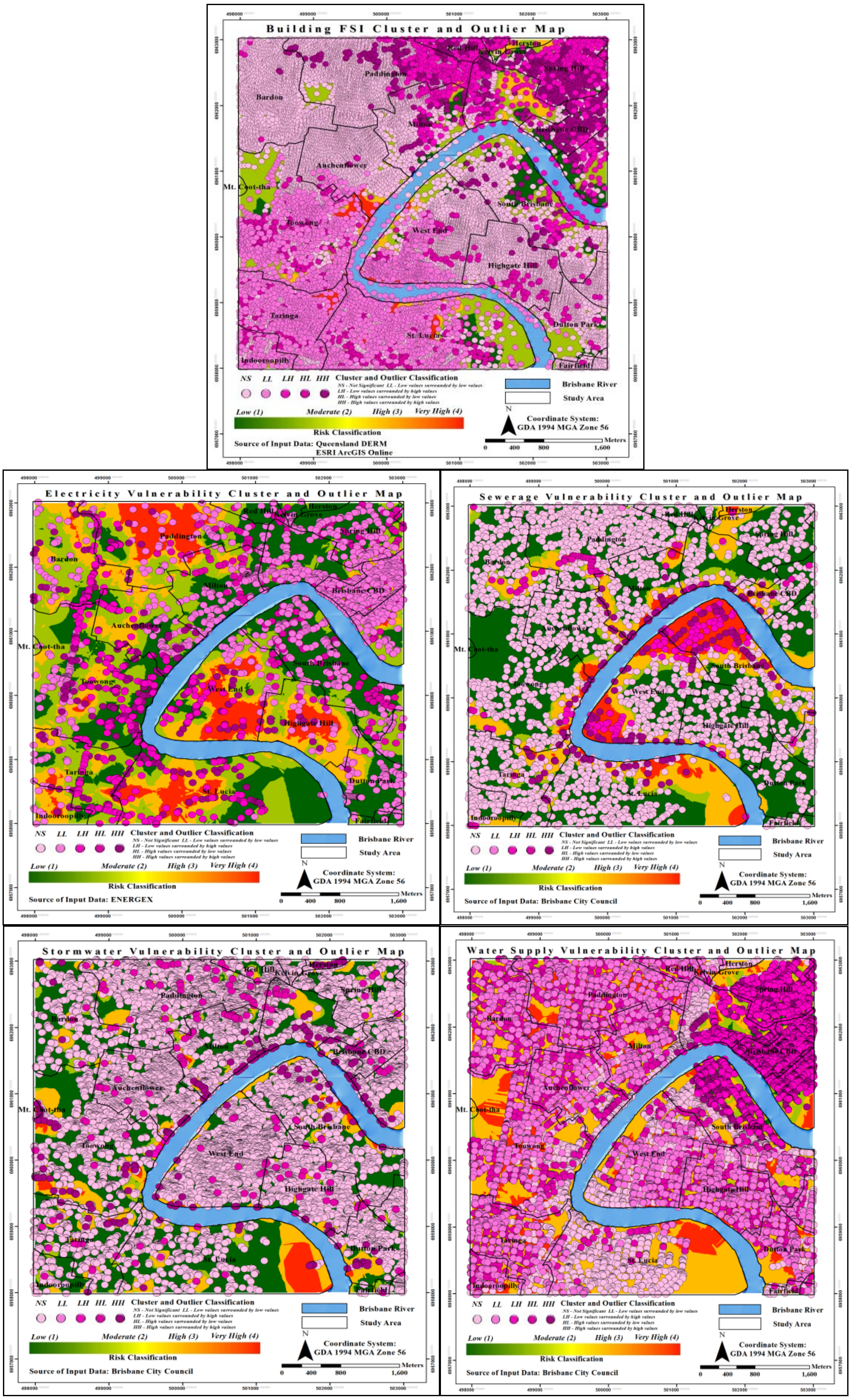


Figure 3.22 The cluster and outlier (CO) maps of critical infrastructures physical vulnerability indicating variables (building FSI, top; electricity, middle left; sewerage, middle right; stormwater, lower left; and water supply, lower right)

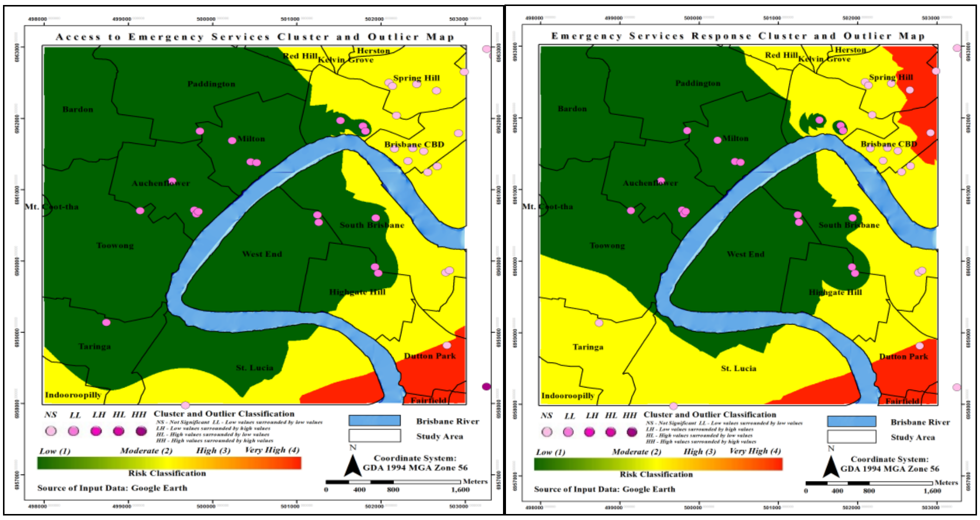


Figure 3.23 The cluster and outlier (CO) maps of social vulnerability indicating variables (access to emergency services, left; emergency services response time, right)

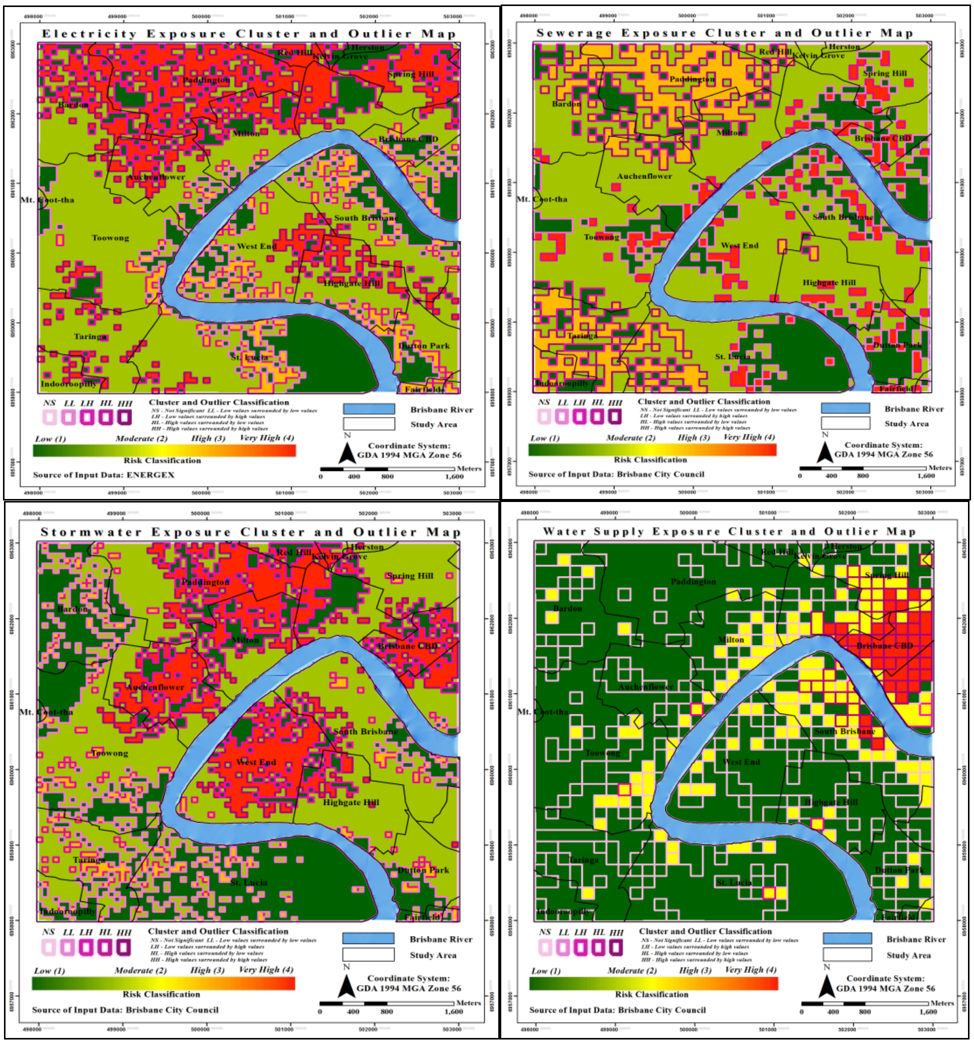


Figure 3.24 The cluster and outlier (CO) maps of critical infrastructures exposure indicating variables (electricity, upper left; sewerage, upper right; stormwater, lower left; and water supply, lower right)

3.3.7 Hot Spot Analysis

Whilst the application of spatial autocorrelation techniques such as the global Moran's I and local Moran's I were significantly useful in this study, these analytical tools however provided spatial clustering of objects of uncertain number of classes for risk classification when applied to heritage sites. Consequently, classes of less than two caused uncertainty in assigning the ordinal values for the perceived flood risk during the assessment process. The hot spot analysis was then operationalised in this study to address this issue and applied in the exposure assessment of heritage sites.

In this study, hot spot analysis was a tool used to calculate the Getis-Ord Gi* statistic by looking each heritage feature within the context of neighbouring features and identified statistically significant spatial clusters of high and low values (ESRI 2011). The Getis-Ord local statistic was measured using the following equations (ESRI 2011) with the classified result shown in Figure 3.25.

$$G_i^* = \frac{\sum_{j=1}^{n} \omega_{i,j} x_j - \bar{X} \sum_{j=1}^{n} \omega_{i,j}}{s \sqrt{\frac{\left[n \sum_{j=1}^{n} \omega_{i,j}^2 - \left(\sum_{j=1}^{n} \omega_{i,j} \right)^2 \right]}{n-1}}} \qquad \text{Eq. 3.24}$$

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \qquad \text{Eq. 3.25}$$

$$s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \qquad \text{Eq. 3.26}$$

where:

x_j is the attribute value for heritage feature j

$\omega_{i,j}$ is the spatial weight between heritage feature i and j

n is the total number of heritage features

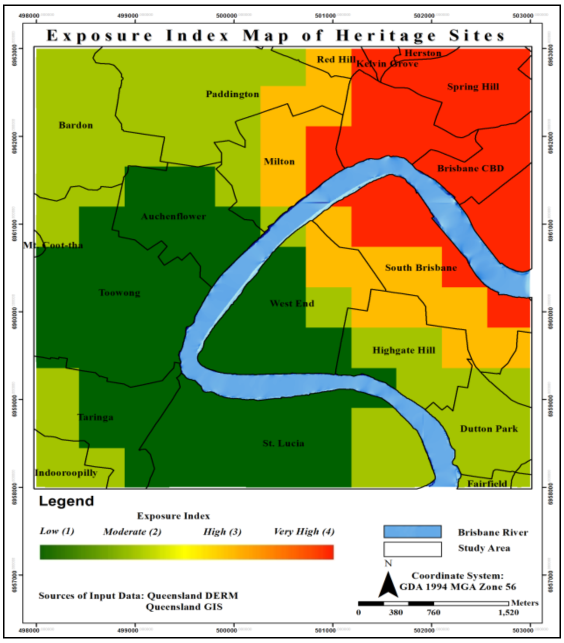


Figure 3.25 The heritage infrastructure exposure index map

3.3.8 Line Statistics

Line statistics are a simple analytical tool in GIS but their importance in the risk analysis of roads and rails cannot be understated in this study. Superimposed with the flood hazard index layer described in Section 3.3.1, the vulnerability of roads and rails to January 2011 flood was identified as shown in Figure 3.26 (foreground). From this map, dark blue lines indicate roads and rails. Its vulnerability indices were classified such as 1 being low and 4 being very highly exposed to the flood hazard.

After having assessed the risk index for the roads and rails network, the neighborhood statistic of the line features was calculated using the Line Statistics tool in ArcGIS to create a 5m-gridded layer. ESRI (2011) defined Line Statistics as a tool that calculates a statistic on the attributes of lines in a circular neighborhood around each output cell. Using mean as the type of statistic, the generated 5m-gridded vulnerability index map of roads and rails network is shown in Figure 3.26 (background).

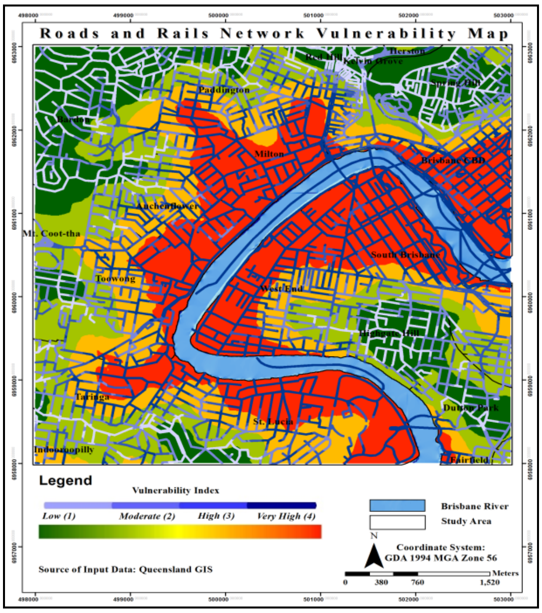


Figure 3.26 The roads and rails vulnerability index map

3.4 Summary and Conclusion

This study applied and developed a variety of analytical tools needed to transform and standardise the indicating variables of hazard, vulnerability, and exposure. Table 3.11 provides the summary of those techniques employed.

Table 3.11 Procedural summary of the transformation and standardisation of indicating variables

Flood Risk and Adaptation Capacity Component	Thematic Layer	Transformation and Standardisation Procedure	Desired Output
Flood Hazard	LIDAR point	1. Created terrain geodatabase file in ArcCatalog; and 2. Transformed terrain dataset to raster with 3D Analyst Tools.	High resolution 5m-gridded digital elevation model (DEM)
	Defined Flood Level (DFL) and January 2011 flood extent	Combined with DEM, continuous DFL and 2011 flood extent were reclassified with fuzzy "small" membership tool of Spatial Analyst.	5m-gridded maps of DFL and January 2011 flood extent
Biological, Chemical, Building Damage, and Electricity Hazards	Point locations of biological, building damage, chemical, and electricity hazards	1. Individually evaluated the expressed patterns of these hazards with spatial autocorrelation (i.e. Global Moran's I); 2. Evaluated the appropriate distance bands using the z-score results from Global Moran's I and used them to run the Cluster and Outlier Analysis (i.e. Anselin Local Moran's I) to identify spatial clusters for each hazard; and 3. Cluster and outlier types were	5m-gridded maps of biological, building damage, chemical, and electricity hazards collectively identified in this study as consequential hazards

Flood Risk and Adaptation Capacity Component	**Thematic Layer**	**Transformation and Standardisation Procedure**	**Desired Output**
		interpolated with the Inverse Distance Weighted (IDW) technique of the Spatial Analyst tool.	
Physical Vulnerability	Building Floor Space Index • LIDAR point • ArcGIS Online high resolution satellite and aerial imagery	1. Digitised almost 17,000 buildings to achieve highly accurate 2D data from LIDAR data and aerial/satellite imagery; 2. Created a building geodatabase in ArcCatalog; 3. Added surface information from LIDAR data; 4. Transformed terrain dataset to raster with 3D Analyst tools; 5. Performed summary statistics geoprocessing to calculate mean heights of the buildings; 6. Analysed the urban fabrics by calculating the building floor space index; 7. Evaluated the expressed patterns of the buildings with spatial autocorrelation (i.e. Global Moran’s I); 8. Evaluated the appropriate distance bands using the z-score results from Global Moran’s I and used them to run the Cluster and Outlier Analysis (i.e. Anselin Local Moran’s I) to identify spatial clusters of buildings; and 9. Cluster and outlier types were interpolated with the Inverse Distance Weight (IDW) technique of the Spatial Analyst tool.	High resolution 5m-gridded building floor space index map
	Estimated Period of Settlement	Transformed period of settlement tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst	5m-gridded period of settlement map
	Electricity Sewerage Stormwater Water Supply	1. Extracted the critical infrastructure junctions/ nodes from the network; 2. Collect events tool of spatial statistics was used to create weighted counts of the infrastructure junctions; 3. Spatial autocorrelation techniques (i.e. Global Moran’s I and Anselin Local Moran’s I) were performed to	5m-gridded physical vulnerability maps

Flood Risk and Adaptation Capacity Component	**Thematic Layer**	**Transformation and Standardisation Procedure**	**Desired Output**
Physical Vulnerability		analyse the cluster and outlier; and 4. Assigned ordinal values to cluster and outlier types and then interpolated with the Inverse Distance Weighted (IDW) technique of the Spatial Analyst tool.	
	Roads and Rails	1. Roads and rails network layer was overlaid with the flood hazard layer; and 2. Performed line statistics analysis.	5m-gridded roads and rails network vulnerability map
Social Vulnerability	Population by Age	Transformed population by age tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded population by age map
	Total Count of Registered Businesses	Transformed the total count of registered businesses tabular data into vector map and standardised with fuzzy “small” membership tool of Spatial Analyst.	5m-gridded total count of registered businesses map
	Educational Qualification	Transformed the percentage of persons with educational qualification tabular data into vector map and standardised with fuzzy “small” membership tool of Spatial Analyst.	5m-gridded educational qualification map
	Point locations of emergency services (police stations, hospitals, fire and rescue stations, and January 2011 evacuation centre)	1. Point distance tool of proximity analysis was used to determine the average distance of emergency services to the geometric centroids of all buildings and calculated the average response time using 30kph driving speed; 2. Collect events tool of spatial statistics was used to create weighted points of coincident features of emergency access and response time; 3. Spatial autocorrelation techniques (i.e. Global Moran’s I and Anselin Local Moran’s I) were performed to cluster the emergency features; and 4. Cluster and outlier types were interpolated with the Inverse Distance Weight (IDW) technique of the Spatial	5m-gridded maps of emergency services accessibility and response time

Flood Risk and Adaptation Capacity Component	**Thematic Layer**	**Transformation and Standardisation Procedure**	**Desired Output**
		Analyst tool.	
Social Vulnerability	SEIFA (IEO, IER, IRSAD, & IRSD)	Transformed the 2011 SEIFA (IEO, IER, IRSAD, and IRSD) tabular data into vector data and standardised with fuzzy “small” membership tool of Spatial Analyst.	5m-gridded maps of IEO, IER, IRSAD, and IRSD
	Insurance (Home and Content)	Transformed insurance tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded insurance map
	Persons in Need of Assistance	Transformed the percentage of persons in need of assistance tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded persons in need of assistance map
	No Vehicles	Transformed the percentage of occupied dwellings without vehicles tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded no vehicle map
	Residential Tenure (Renting)	Transformed residential tenure tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded residential tenure map
	Total Building Value	Transformed total building value tabular data into vector map and standardised with fuzzy “small” membership tool of Spatial Analyst.	5m-gridded total building value map
	Unemployment Rate	Transformed unemployment rate tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded unemployment map
	Volunteers	Transformed the percentage of volunteers tabular data into vector map and standardised with fuzzy “small” membership tool of Spatial Analyst.	5m-gridded volunteer map
	Weekly Personal Income	Transformed the percentage of persons with weekly income < $400 tabular data into vector map and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded personal weekly income map

Flood Risk and Adaptation Capacity Component	Thematic Layer	Transformation and Standardisation Procedure	Desired Output
Social Vulnerability			
Exposure	Flooded Residential and Commercial Properties	1. Counts of January 2011 flooded properties from news reports were transformed into vector map using land use as the base map; and 2. Standardised the flooded properties map with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded flooded residential and commercial properties map
	Estimated Resident Population and Annual Population Growth Rate	Transformed estimated resident population and annual population growth rate tabular data into vector maps and standardised with fuzzy “large” membership tool of Spatial Analyst.	5m-gridded population and annual growth rate maps
	Electricity	Separately performed quadrat analysis and then standardised with spatial autocorrelation techniques or hot spot analysis.	5m-gridded heritage sties and critical infrastructures exposure maps
	Sewerage		
	Stormwater		
	Heritage Sites		
	Water Supply		

This Chapter demonstrated the different applications of spatially-explicit analytical tools of transforming and standardising flood risk and climate adaptation capacity indicating variables sourced from varying spatial information. The selection made on the statistical tools depends on the geographic types and attributes of indicating variables to be analysed. In the execution of the statistical tool, extra care was given attention in such a way not to lose its significance in relation to the established assumptions.

The results obtained from those analytical tools as inputs for simulating flood risk and adaptation capacity showed how the methodology can be used with success by fully exploiting the available spatial information. The issue of representing flood risk and climate adaptation capacity indicating variables was fully addressed in this Chapter through the generation of hazard, vulnerability, and exposure indices in raster format. The steps involved in calculating these indices were fairly straightforward to some datasets and complex to other datasets. This implies that there is no single spatially-explicit analytical tool that can deal with variable spatial information.

After having all the indicating variables transformed and standardised into raster/gridded format, the next question addressed in this study focused on whether all of the indicating variables be included in the flood risk and climate adaptation capacity assessments. The early part of the next Chapter explores the response to this query.

Chapter 4

USING SPATIAL MODELLING TO DEVELOP FLOOD RISK AND CLIMATE ADAPTATION CAPACITY METRICS

4.1 Introduction

Chapter 3 discussed the spatially complex and statistical processes of transforming and standardising a set of flood risk and climate adaptation capacity indicating variables into raster datasets. The next step is a novel approach of quantifying flood risk and climate adaptation capacity indices/metrics within which this Chapter is designed for. In quantifying the indices/metrics, four main contributions to computational techniques were deployed: (1) the Artificial Neural Network (ANN) based on Kohonen's Self-Organising Map (SOM) architecture or otherwise known as Self-Organising Neural Network (SONN), (2) joint conditional probable weights calculation based on Bayesian probability rule, (3) weighted overlay, and (4) fuzzy gamma overlay. Also significant in Chapter 4 is the prescriptive modelling of disaster risk reduction and climate adaptation strategies within the spatial framework.

In most flood risk and climate adaptation capacity assessments, developing a comprehensive set of metrics is challenging due to a wide variety of climate adaptations as well as the dynamic nature of various environmental and socio-economic factors (Szlafsztein 2008). This research problem is further exacerbated by inductive argumentation which particularly pertains to the sufficiency of indicating variables and availability of statistical models in climate risk assessment. When these indicating variables are aggregated with deductive approach (e.g. expert judgment) or by normative approach (e.g. equal weighting), the delivery of robust results is an issue due to subjective judgments in the former case and the multi-dimensionality of variables to different stakeholders in the latter case (Hinkel 2011). This issue is further aggravated by the process of selecting the indicating variables to indicate flood risk and its application to adaptation capacity assessment. This study had devised an ArcGIS-MATLAB algorithm interface in working the self-organising neural network (SONN) to select appropriate indicating variables and aggregate them with joint conditional probable weights based on Bayesian theory for flood risk and climate adaptation capacity modelling.

The research issues and justifications on the use of the above computational techniques are found in the subsequent sections and discussed more in Chapter 2 (Literature Review).

4.2 Research Methods

4.2.1 Application of Artificial Neural Network - Self-Organising Neural Network

A variety of "intelligent" systems has been developed to advance research in numerous scientific disciplines. While modern digital computers can outperform humans in difficult numeric computation and manipulation; however, the latter can effortlessly solve complex perceptual problems at a high speed and extent (Jain *et al.* 1996). The remarkable difference in their performance lies in the biological neural system architecture in humans (Jain *et al.* 1996), which is typically absent in computation modelling system.

Neural networks or more precisely known as artificial neural networks (ANN) are a branch of artificial intelligence (Gardner and Dorling 1998) which attempts to simulate the networks of nerve cell (neurons) of the biological (human or animal) central nervous system (Graupe 2007). The application of ANN in various researches was proposed based on modern biology research relating to human brain tissue, which can be used to simulate neural activity in the human brain (Markopoulos *et al.* 2008, Feng and Lu 2010). The rough analogy between artificial neuron and biological neuron is that the connections between nodes represent the axons and dendrites, the connection weights represent the synapses, and the threshold approximates the activity in the soma (Jain *et al.* 1996, Basheer and Hajmeer 2000). Figure 4.1 demonstrates *n* biological neurons with various signals of intensity *x* and synaptic strength *w* feeding into a neuron with a threshold of *b* (Basheer and Hajmeer 2000).

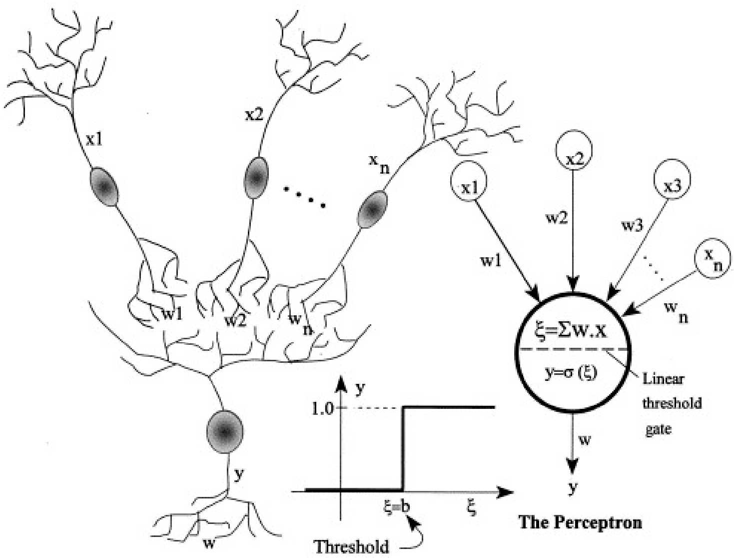


Figure 4.1 The analogy between artificial neuron and biological neuron (after Basheer and Hajmeer 2000)

In the application of Self-Organising Neural Network (SONN) for disaster risk reduction, three most important strategic goals were taken into consideration following the adoption made by the participants at the 2005 World Conference on

Disaster Reduction in Hyogo, Japan based on Hyogo Framework for Action 2005-2015. These include (UNISDR 2005):

1. The more effective integration of disaster risk considerations into sustainable development policies, planning and programming at all levels, with special emphasis on disaster prevention, mitigation, preparedness and vulnerability reduction;
2. The development and strengthening of institutions, mechanisms and capacities at all levels, in particular at the community level, that can systematically contribute to building resilience to hazards; and

3. The systematic incorporation of risk reduction approaches into the design and implementation of emergency preparedness, response and recovery programs in the reconstruction of affected communities.

The main question for disaster reduction manager generally involves knowledge on how to integrate disaster risk considerations such as climate adaptation at the federal, state, or local level and the systematic incorporation of preparedness, mitigation, response and recovery measures. This study proposed to solve the issue by utilising spatial analytical tools in combination with self-organising neural network. The approach was implemented by exploring the multi-parametric assessment of flood risk and climate adaptation capacity with Kohonen's self-organising map (SOM). The standardised variables for flood risk and climate adaptation capacity variables (see Chapter 3) were analysed in the MATLAB workspace.

Kohonen self-organising map (KSOM) is a subtype of the ANN that is particularly useful for visualisation of highly dimensional data (Mele and Crowley 2008). It consists of a competitive layer that allows classification of datasets with any number of dimensions into as many classes as the layer has neurons, which are arranged in a 2D topology (The Mathworks Inc. 2011). In this study, the SOM/SONN was operationalised with four components: 1) input layer referring to the flood risk indicating variables; 2) neuron computation; 3) output layer; and 4) a map of clustered variables (Mele and Crowley 2008) as shown in Figure 4.2.

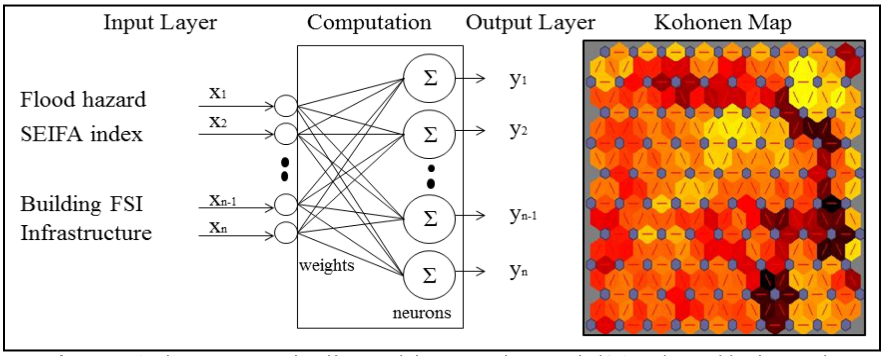


Figure 4.2 The conceptual self-organising neural network (SONN) used in the study

This study used Artificial Neural Network (ANN) with emphasis on Self-Organising Neural Network (SONN) because this computational technique allows multiple variables in both the input and output layers (Feng and Lu 2010). For examples, Wallner *et al.* (2013) designed a regionalisation technique based on self-organising maps to optimise sets of model parameters and relate them with sub-catchment's physical properties. Choi *et al.* (2014) emphasised that the relationship between groundwater samples and variables is found more clearly in using self-organising maps than principal component analysis (PCA); hence, the approach can be successfully used to classify and characterise the groundwater in terms of hydrochemistry and quality. In understanding the effects of landscape and morphometric factors on water quality of reservoirs, Park *et al.* (2014) also applied the technique and found that hydrogeomorphometry of reservoirs and percentages of land cover types have a considerable impact on the water quality. The integration of time element with self-organising map was made possible in the study conducted by Clark *et al.* (2014) such that the method can be applied to a wide variety of datasets and is well suited to ecological and environmental data with missing values and data structures that are changing over time.

To recall, thirty seven (37) indicating variables were standardised in this study (see Chapter 3) and subsequently used in the SOM/SONN analysis: 5 for hazard, 7 for physical vulnerability, 17 for social vulnerability, and 8 for exposure. The consideration of these multiple variables is important since flood risk and adaptation capacity are often functions of various flood hazard, vulnerability, and exposure variables, which form the novelty value of this study. In analysing these variables, vulnerability assessment of individual infrastructure had given particular emphasis.

The advent of geographic information systems has made mapping of flood risk and climate adaptation capacity variables easier by providing tools that manipulate spatial data and allow their integration. However, leaping directly into data integration without initial relational assessment of indicating variables will lead into less accurate modelling and simulation result. Pavlin *et al.* (2010) emphasised that obtaining models can be very challenging because information sources are heterogeneous and noisy, and reliable detection in such settings requires processing of large quantities of noisy information. The goal of this exercise was to address these issues by looking at the patterns and interrelationships that exist among variables using MATLAB, a high-level technical computing language and interactive environment for algorithm development, data visualisation, data analysis, and numeric computation (The Mathworks, Inc. 2011).

The first step in analysing the data in MATLAB was to import the standardised variables in previously saved Tagged Image File Format (TIFF). The import wizard generated the names of the standardised variables specified in Chapter 3 with pertinent descriptions as shown in the following figure.

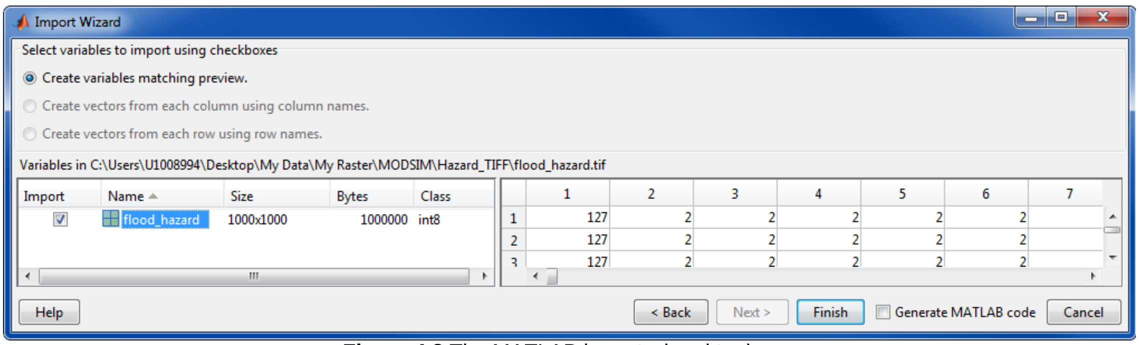


Figure 4.3 The MATLAB import wizard tool

From Figure 4.3, the imported variables are displayed in a 1000x1000 matrix or a rectangular array of numbers with row and column values shown in the right side of the panel. These numerical values represent the perceived level of flood risk described in Chapter 3 (i.e. 1 – low, 2- moderate, 3 – high, 4 – very high). In the matrix, the value “127” represents the null values from the imported TIFF file. Null values in the matrix were automatically generated by MATLAB during the importing process which correspond the Brisbane River in the GIS-based TIFF or raster file.

To remove the undesired null values from the matrix and automatically create an *n x m* array, the following scripts were executed in the MATLAB command window:

$$x_i\ (x_i > 127.) = [\ ];$$
$$c = [\ x_1\ (:), x_2\ (:), \ldots, x_n(:)\ ];$$

where x_i are the flood risk and climate adaptation capacity variables
c is the complete set of variables in a single *n* x *m* array
n is the number of rows
m is the number of columns represented by 37 variables

Including the flood hazard as the base indicating variable, the ith columns in the matrices represent the indicating variables of flood risk and adaptation capacity. Utilising the Neural Network Clustering Tool as shown in Figure 4.4, these variables were grouped or clustered by similarity through the process of classifying a 2-dimension layer of 100 neurons arranged in a 10 x 10 hexagonal grids. To execute the learning topology and distribution of indicating variables, the network was trained with a minimum of two (2) up to a maximum of four (4) using the batch SOM algorithm with 200 epochs as summarised in Table 4.1

Table 4.1 The number of training performed in the neural network

Infrastructure Asset	Number of Training
Electricity	2
Roads and Rails	4
Sewerage	3
Stormwater	3
Water Supply	4
Integrated Infrastructure	4

Taking flood hazard as the basis in the pair-wise comparison, the SOM planes were examined to depict an intuitive pattern of similarity with all indicating variables.

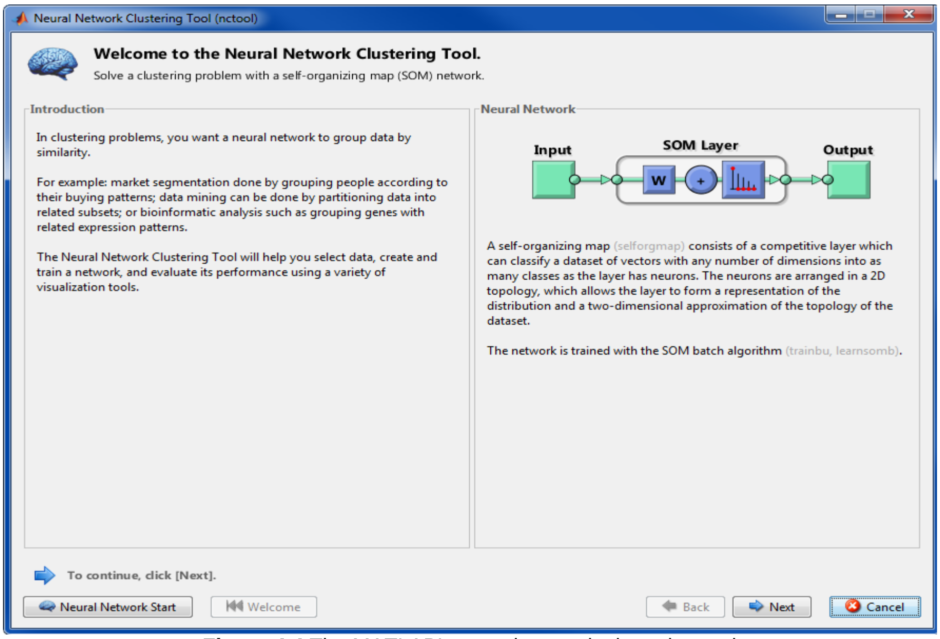


Figure 4.4 The MATLAB's neural network clustering tool

4.2.2 Quantification of Flood Risk and Climate Adaptation Capacity Metrics

Computer-based applications require various conflicting sources of information to be aggregated to form a global contradiction-free system (Gregoire and Konieczny 2006). Probabilistic causal models facilitate the design of robust and flexible modular fusion systems with the help of causal Bayesian networks (Pavlin *et al.* 2010). In this section, a methodology is presented to estimate the joint conditional probable weights of indicating variables that can influence in measuring flood risk and climate adaptation capacity based on Bayesian theorem. This study used Bayesian probability based on the following reasons:

1. The probabilistic framework provides accurate prediction of uncertainties such as in sea level rise and associated inundation levels (Rajabalinejad and Demirbilek 2013);
2. Bayesian combination of models is an interesting tool for flood estimation because it gives preference to different models, depending on the catchment size and on the availability of flood data (Niggli and Musy 2005);
3. Bayesian probabilistic model performs well in providing a foundation for hazard mapping (Hapke and Plant 2010);
4. Direct probabilistic statements can be made about the unknown parameters, thus improving communication with decision makers (Parent and Bernier 2003); and
5. Combined with Markov Chain Monte Carlo (MCMC), the Bayesian method provides a computationally attractive and straightforward technique to develop a full and complete description of the uncertainty in parameters, quantiles and performance metrics (Reis and Stedinger 2005).

4.2.2.1 Calculating Bayesian joint conditional probable weights

From Table 4.2, the values indicated in Bayesian joint conditional probable weight columns were calculated using the following equation:

$$P(FR_i \backslash V_i) = \frac{Pmax\,(FR_i \cap V_i)}{\sum n\ Pmax(FR_i \cap V_i)} \qquad \text{Eq. 4.1}$$

where:

FR is the flood risk represented by flood hazard as an apriori event
V is an indicating variable
i is the level of perceived flood risk (1-low, 2-moderate, 3-high, 4-very high)
Pmax is the maximum probability of an indicating variable
n is the number of indicating variables

These weight values were used in aggregating the indicating variables of hazard, vulnerability, and exposure. The purpose of calculating weights with Bayesian probability was to address the multi-dimensionality issue in the normative argument of equal weights. In the normative argument, the indicating variables are aggregated such that each dimension should be equally important in characterising the state of development (UNDP 1991, 1993; Hinkel 2011). However, vulnerability assessment is not a straightforward exercise because aggregation is complicated as multiple stakeholders value the dimensions in different ways (Hinkel 2011). Within the context of spatial dimension, the development of risk from different indicating variables varies across the space. In community vulnerability assessment, for example, people affected by floods, wetlands lost, damage cost, and adaptation cost are important dimensions to consider (Hinkel 2011).

4.2.2.2 GIS-based weighted overlay analysis

In the geospatial domain, data aggregation can be operationalised using the weighted overlay analytical tool which is available in several GIS software such as ArcGIS. Figure 4.5 shows an example of how weighted overlay analysis was executed in generating hazard index. The values shown in % influence column of the figure were the calculated Bayesian joint conditional probable weights using Equation 4.1 (also see Table 4.2). The weighted overlay technique was also utilised to produce the vulnerability and exposure indices.

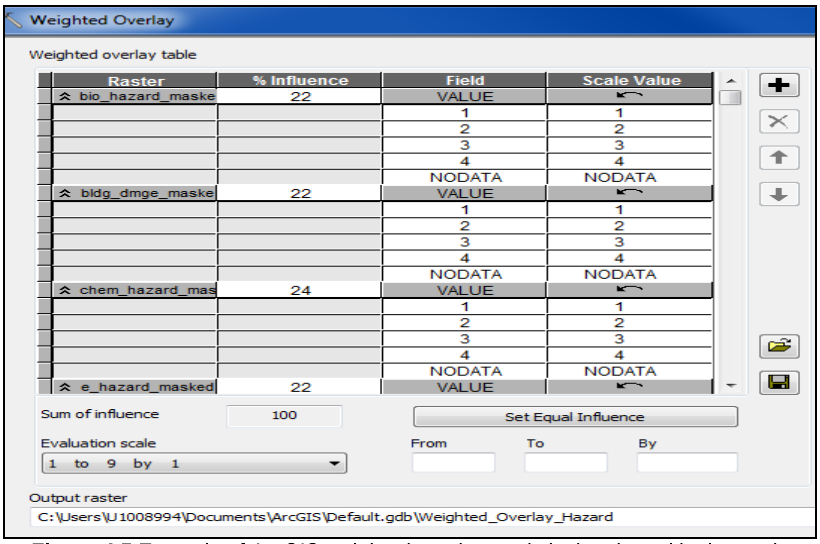


Figure 4.5 Example of ArcGIS weighted overlay analytical tool used in the study

After having generated the hazard, vulnerability and exposure indices, the fuzzy gamma overlay analysis was performed to derive the flood risk index, which in turn used in calculating the climate adaptation capacity index. The choice and justifications on the use of these analytical tools were further discussed in Chapters 2 and 3.

4.3. Results and Discussions

4.3.1 Generated SOM/SONN planes by infrastructure assets

Shown in Figures 4.6 to 4.11 below are the generated SOM/SONN planes of all indicating variables by infrastructure asset and integrated infrastructure assets. Using flood hazard as the basis in the pair-wise comparison, results of the analysis revealed intuitive pattern of similarity and dissimilarity among the indicating variables. From Table 4.2, the indicating variables marked with “x” were excluded from further analysis because they have general patterns dissimilar to flood hazard. However, when all these indicating variables were integrated (Figure 4.10), the pair-wise comparison showed that all indicating variables were included for further analysis because they have not shown clear patterns of dissimilarity.

Furthermore, Table 4.2 summarises that 27 out of 30 indicating variables from electricity, roads and rails, sewerage, and stormwater; 28 out of 30 from water supply; and 30 out of 30 from integrated infrastructures were selected or included in the quantification of flood risk and climate adaptation capacity metrics.

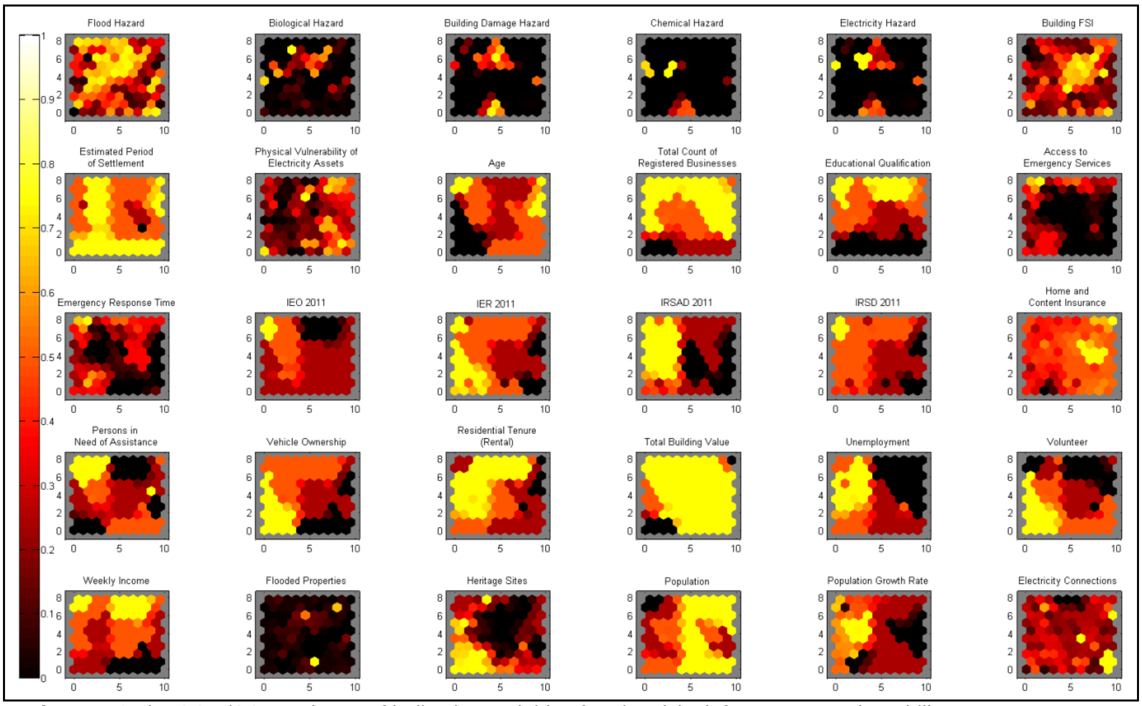


Figure 4.6 The SOM/SONN planes of indicating variables for electricity infrastructure vulnerability assessment

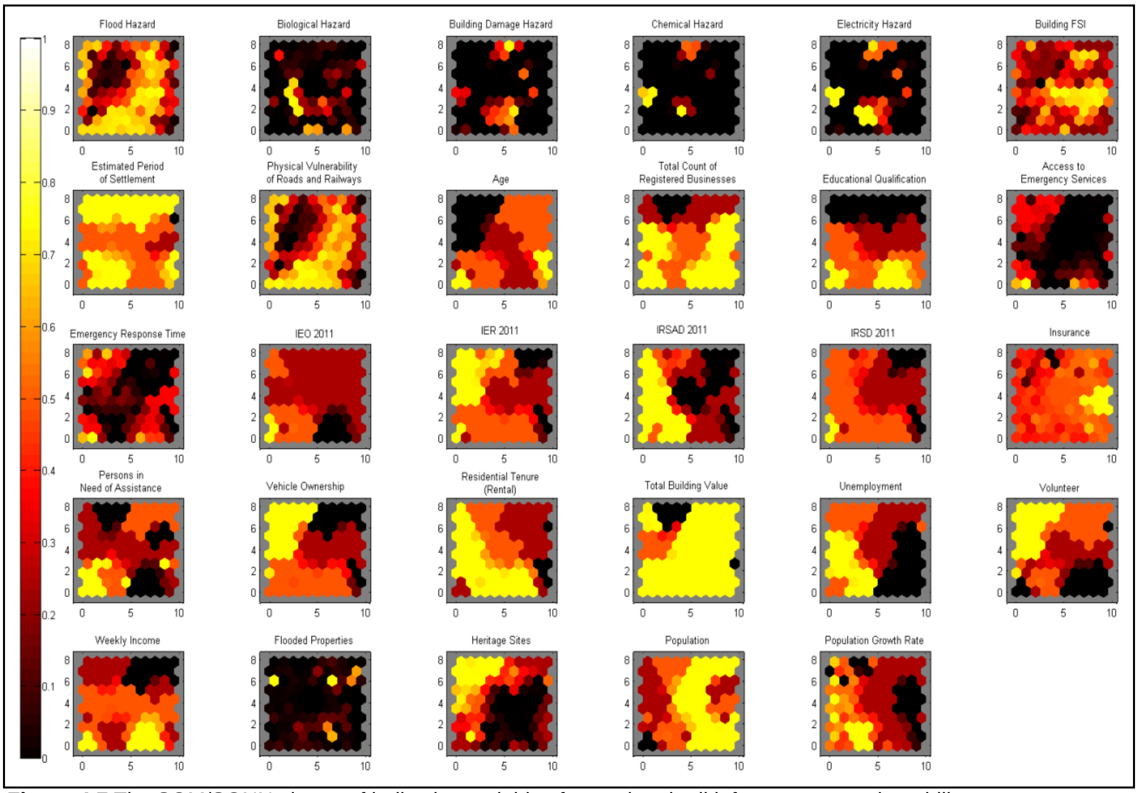


Figure 4.7 The SOM/SONN planes of indicating variables for road and rail infrastructures vulnerability assessment

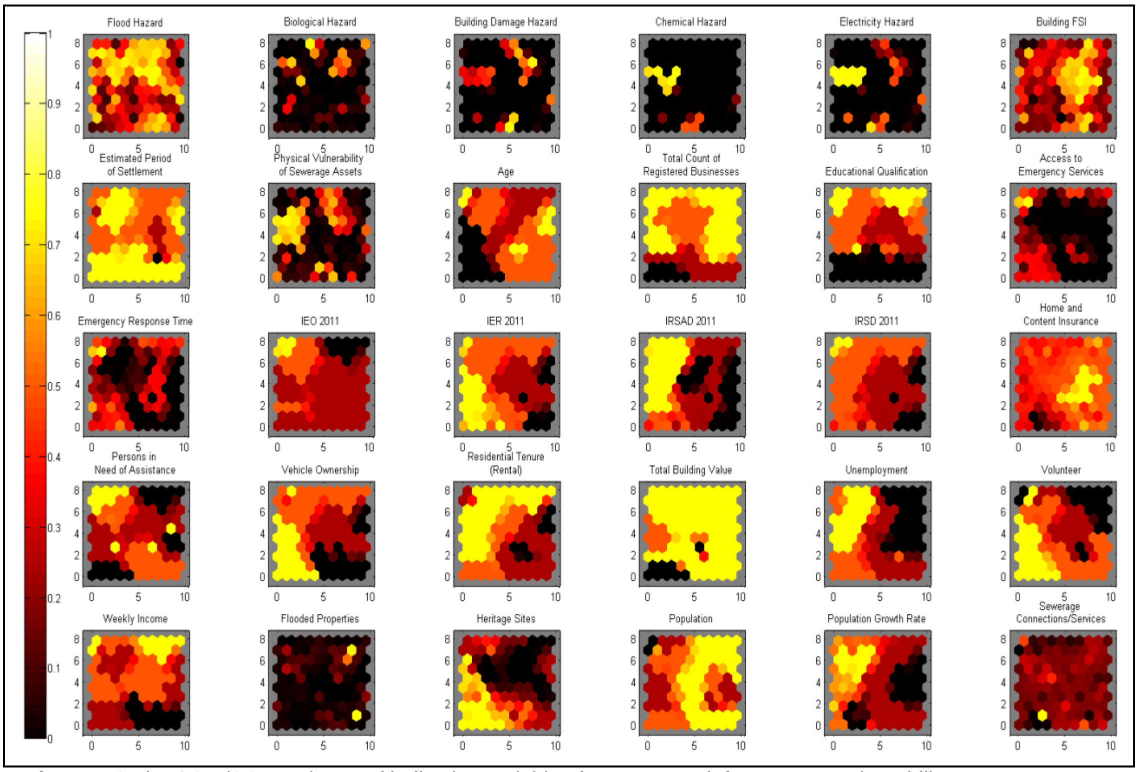


Figure 4.8 The SOM/SONN planes of indicating variables for sewerage infrastructure vulnerability assessment

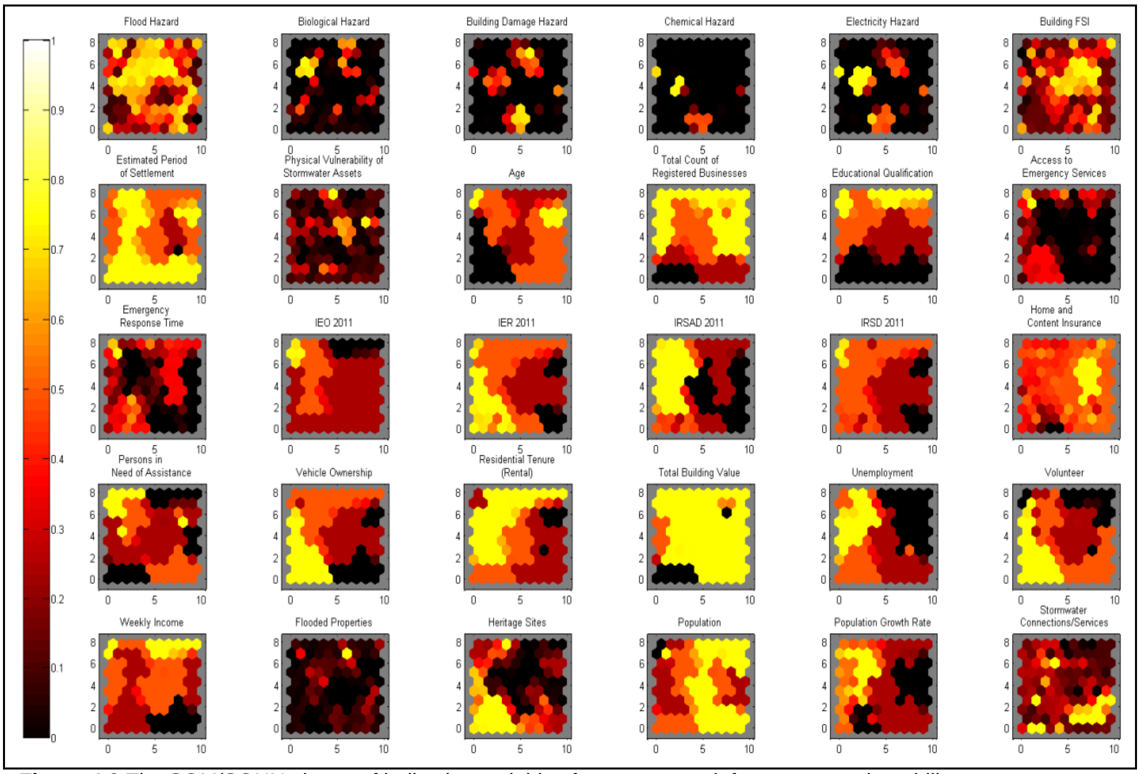


Figure 4.9 The SOM/SONN planes of indicating variables for stormwater infrastructure vulnerability assessment

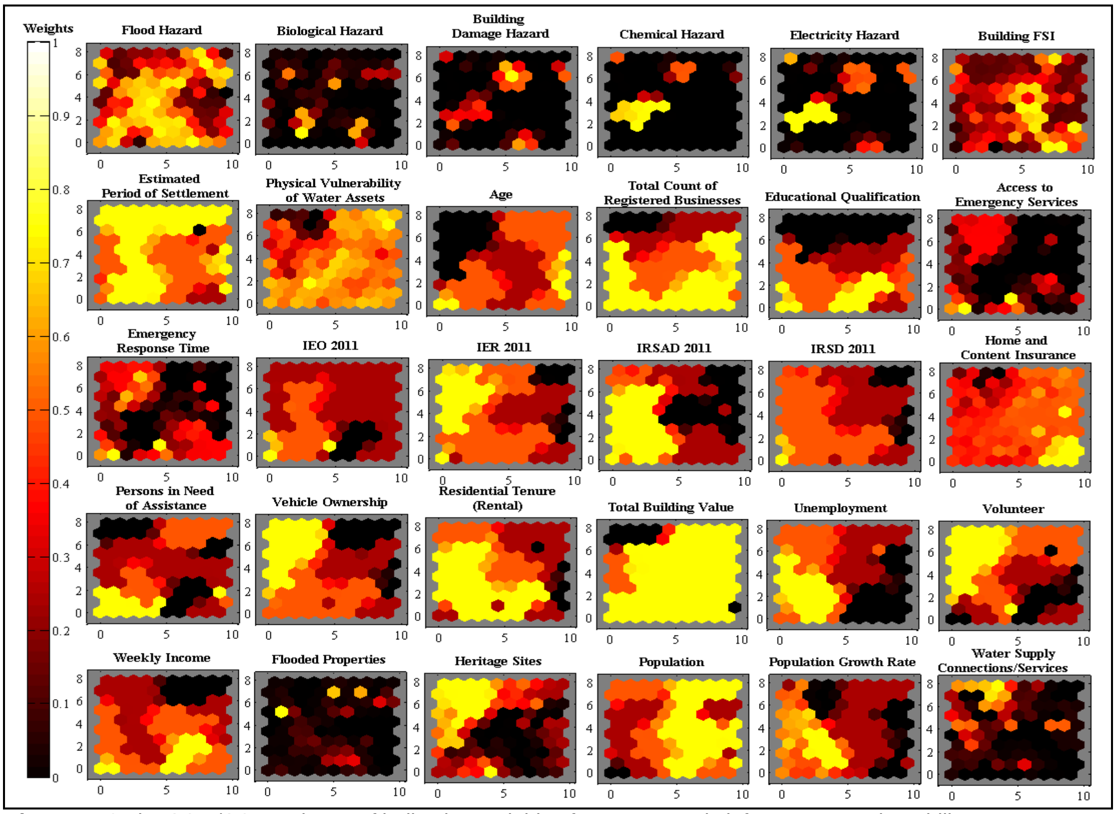


Figure 4.10 The SOM/SONN planes of indicating variables for water supply infrastructure vulnerability assessment

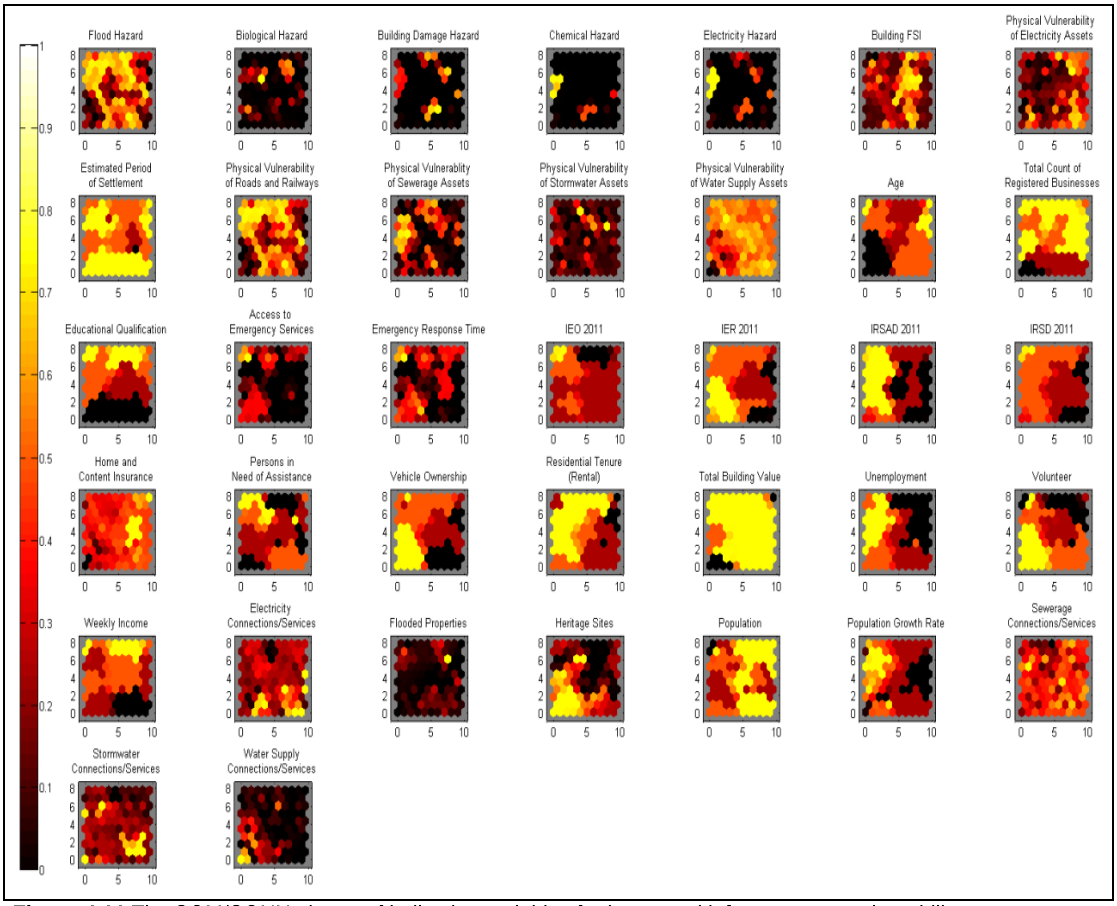


Figure 4.11 The SOM/SONN planes of indicating variables for integrated infrastructures vulnerability assessment

Table 4.2 The indicating variables used in the SOM/SONN analysis and corresponding Bayesian joint conditional probable weights

Flood Risk/ Adaptation Capacity Component	Selected Indicating Variable	Bayesian Joint Conditional Probable Weight					
		Electricity	Roads & Rails	Sewerage	Storm Water	Water Supply	Integrated Infrastructures
Hazard	Biological Hazard	0.22	0.22	0.22	0.22	0.22	0.22
	Building Damage Hazard	0.22	0.22	0.22	0.22	0.22	0.22
	Chemical Hazard	0.24	0.24	0.24	0.24	0.24	0.24
	Electricity Hazard	0.22	0.22	0.22	0.22	0.22	0.22
	Flood Hazard	0.10	0.10	0.10	0.10	0.10	0.10
Physical Vulnerability	Building FSI	0.35	0.37	0.42	0.28	0.30	0.13
	Vulnerability of Electricity	0.28	NA	NA	NA	NA	0.10
	Period of Settlement	0.37	0.38	x	0.30	0.39	0.14
	Vulnerability of Roads & Rails	NA	0.25	NA	NA	NA	0.09
	Vulnerability of Sewerage	NA	NA	0.58	NA	NA	0.18
	Vulnerability of Stormwater	NA	NA	NA	0.42	NA	0.19
	Vulnerability of Water Supply	NA	NA	NA	NA	0.31	0.17
Social Vulnerability	Age	0.06	0.06	0.06	0.06	0.07	0.05
	Total Count of Registered Businesses	0.08	0.08	0.07	0.08	0.08	0.07
	Educational Qualification	0.05	0.05	0.04	0.05	0.05	0.04
	Access to Emergency Services	x	x	0.09	x	x	0.09
	Emergency Response Time	x	x	0.07	x	x	0.07
	IEO 2011	0.07	0.07	0.06	0.07	0.07	0.06
	IER 2011	0.06	0.06	0.04	0.06	0.06	0.05
	IRSAD 2011	0.05	0.05	0.04	0.05	0.05	0.05
	IRSD 2011	0.07	0.07	0.06	0.07	0.07	0.06
	Home and Content Insurance	0.09	0.09	0.06	0.09	0.08	0.07
	Persons in Need of Assistance	0.06	0.06	0.04	0.06	0.06	0.05
	Vehicle Ownership	0.05	0.05	0.04	0.05	0.05	0.04
	Residential Tenure (Rental)	0.07	0.07	0.05	0.07	0.07	0.06
	Total Building Value	0.13	0.13	0.10	0.13	0.13	0.11
	Unemployment	0.05	0.05	0.04	0.05	0.05	0.04
	Volunteer	0.05	0.05	x	0.05	0.05	0.04
	Weekly Income	0.06	0.06	0.04	0.06	0.06	0.05

Flood Risk/ Adaptation Capacity Component	**Selected Indicating Variable**	**Bayesian Joint Conditional Probable Weight**					
		Electricity	**Roads & Rails**	**Sewerage**	**Storm Water**	**Water Supply**	**Integrated Infrastructures**
Exposure	Electricity Connections	0.23	NA	NA	NA	NA	0.12
	Flooded Properties	0.39	0.51	0.38	0.40	0.31	0.20
	Heritage Sites	x	x	x	x	0.12	0.08
	2011 Population	0.20	0.26	0.20	0.21	0.16	0.10
	Population Growth Rate	0.18	0.23	0.18	0.18	0.14	0.09
	Sewerage Connections	NA	NA	0.24	NA	NA	0.13
	Stormwater Connections	NA	NA	NA	0.21	NA	0.10
	Water Supply Connections	NA	NA	NA	NA	0.27	0.18
Ratio	**Selected (No.)**	27	27	27	27	28	30
	Total (No.)	30	30	30	30	30	30

x – Excluded from further analysis
NA – Not applicable

4.3.2 Flood Risk and Climate Adaptation Capacity Models

Applying the weighted overlay analytical tool as discussed in Section 4.2.2.2, the physical vulnerability, social vulnerability, and exposure indices of the study area were calculated. Figure 4.12, Figures 4.13 to 4.18, Figures 4.19 to 4.24, and Figures 4.25 to 4.30 show the weighted overlay maps of hazard, physical vulnerability, social vulnerability, and exposure indices, respectively. From here onwards, the maps are presented using uniform symbols such that areas from green to red represent low to very high hazard/vulnerability/exposure, respectively.

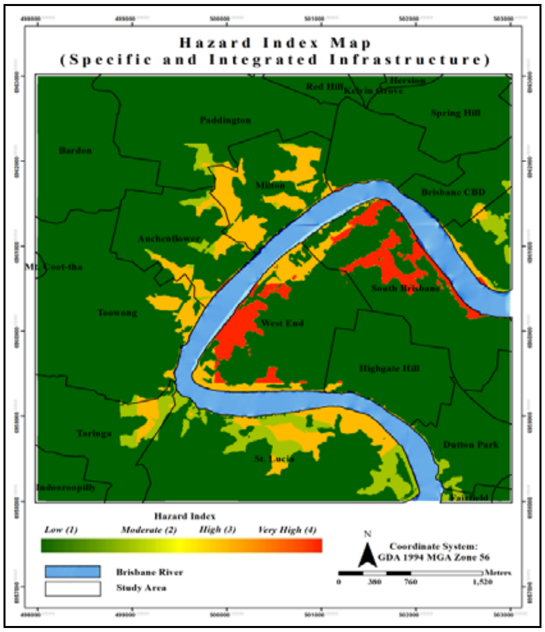


Figure 4.12 The weighted hazard index map for assessing specific and integrated infrastructures

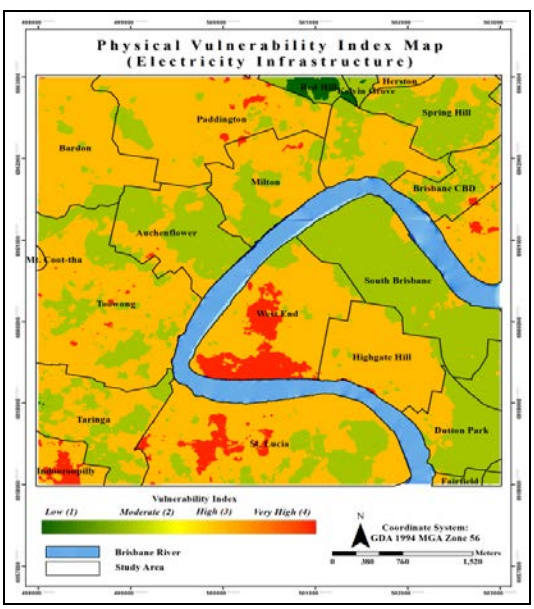


Figure 4.13 The weighted physical vulnerability index map for assessing electricity infrastructure

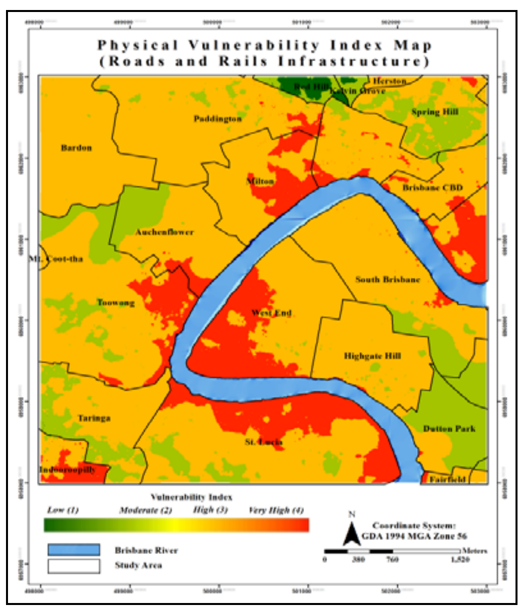


Figure 4.14 The weighted physical vulnerability index map for assessing road and rail infrastructures

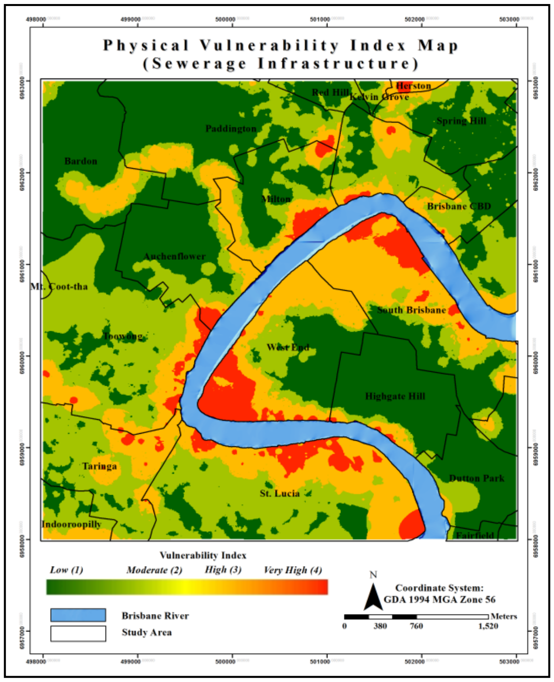


Figure 4.15 The weighted physical vulnerability index map for assessing sewerage infrastructure

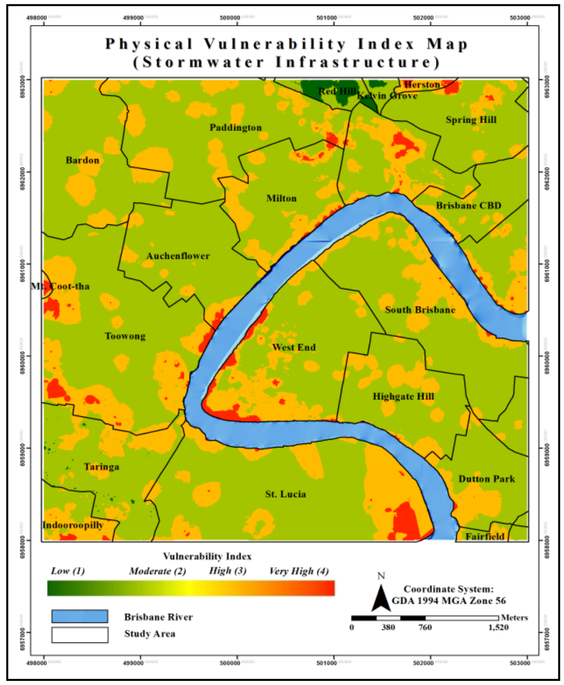


Figure 4.16 The weighted physical vulnerability index map for assessing stormwater infrastructure

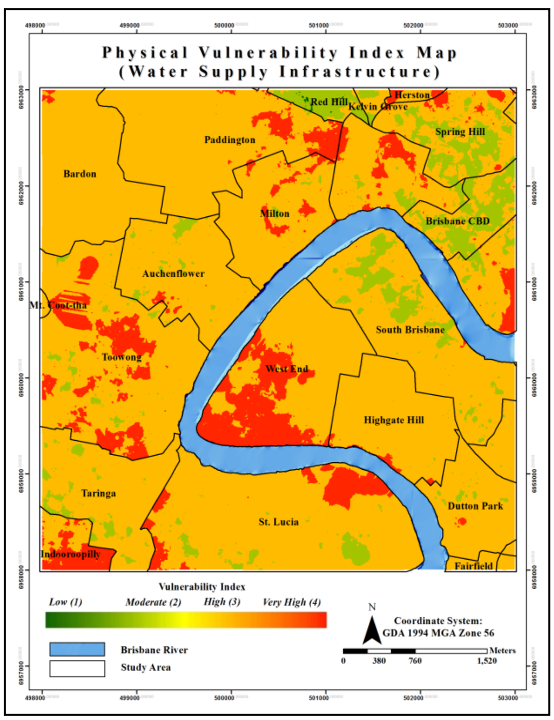


Figure 4.17 The weighted physical vulnerability index map for assessing water supply infrastructure

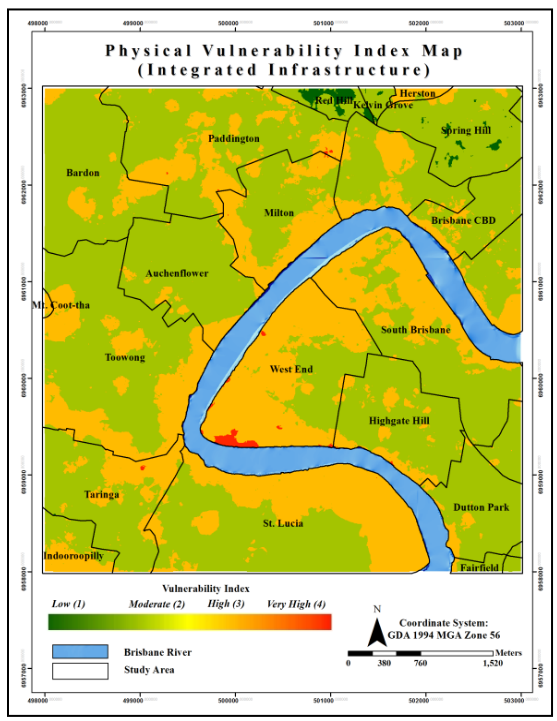


Figure 4.18 The weighted physical vulnerability index map for assessing the integrated infrastructures

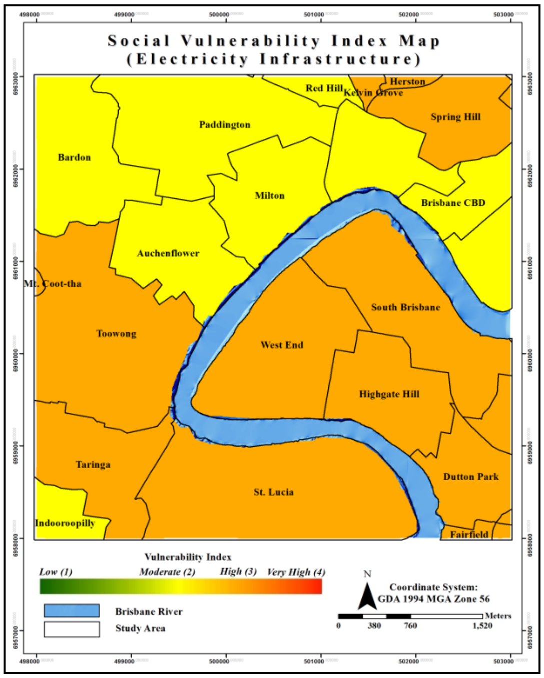


Figure 4.19 The weighted social vulnerability index map for assessing electricity infrastructure

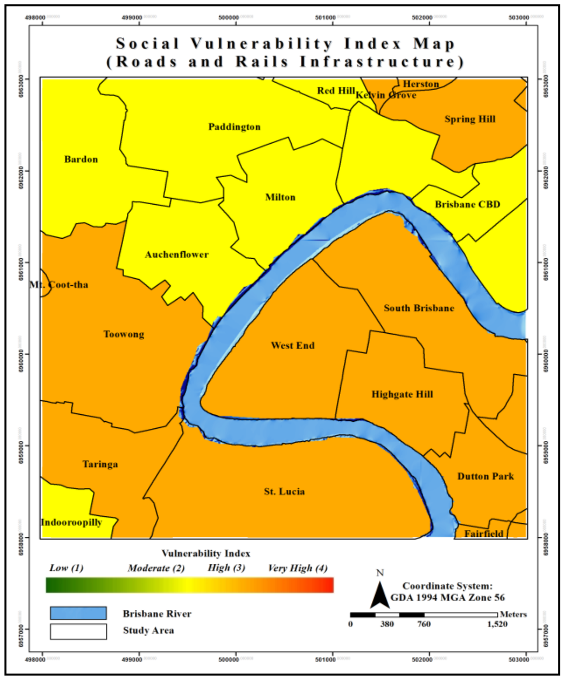


Figure 4.20 The weighted social vulnerability index map for assessing road and rail infrastructures

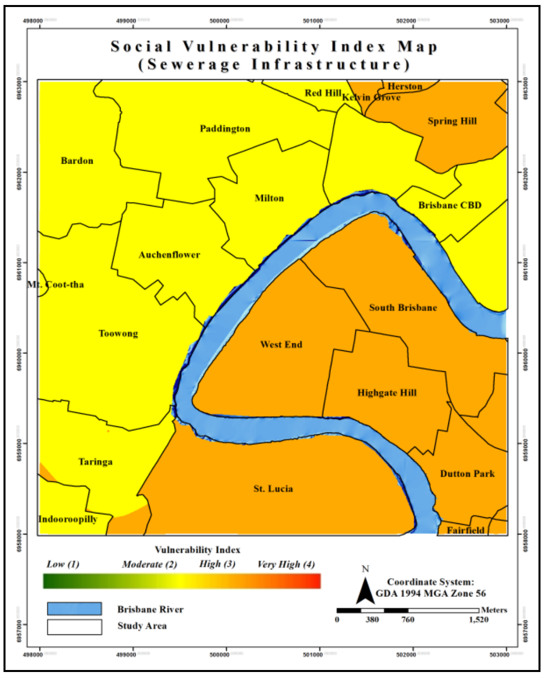


Figure 4.21 The weighted social vulnerability index map for assessing sewerage infrastructure

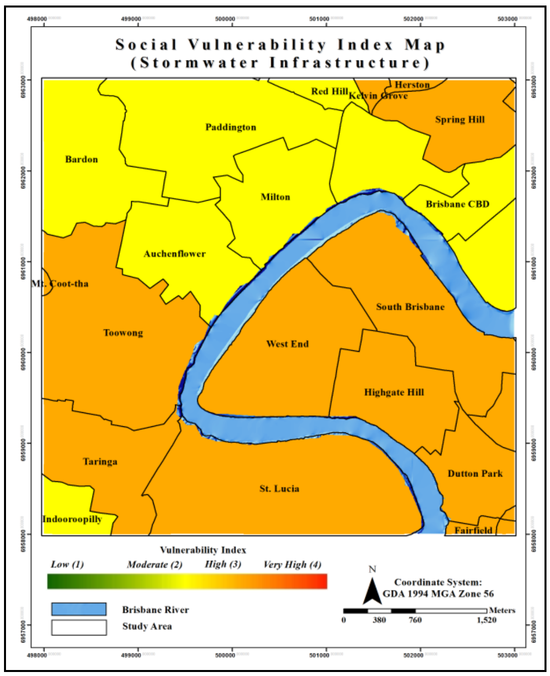


Figure 4.22 The weighted social vulnerability index map for assessing stormwater infrastructure

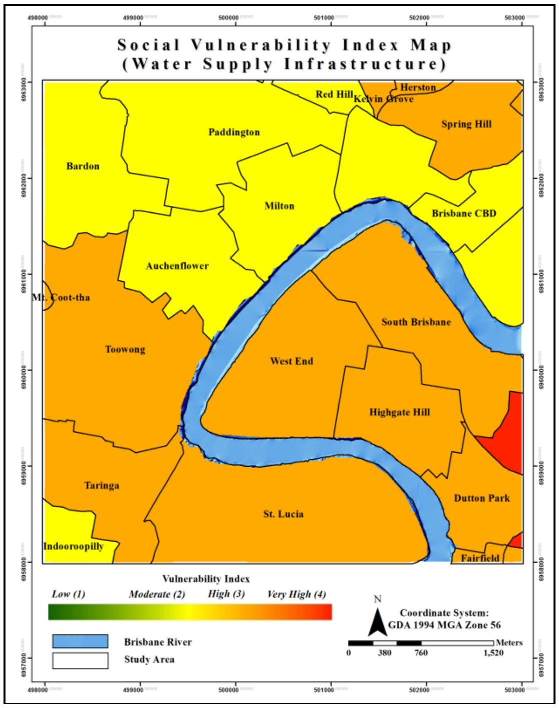


Figure 4.23 The weighted social vulnerability index map for assessing water supply infrastructure

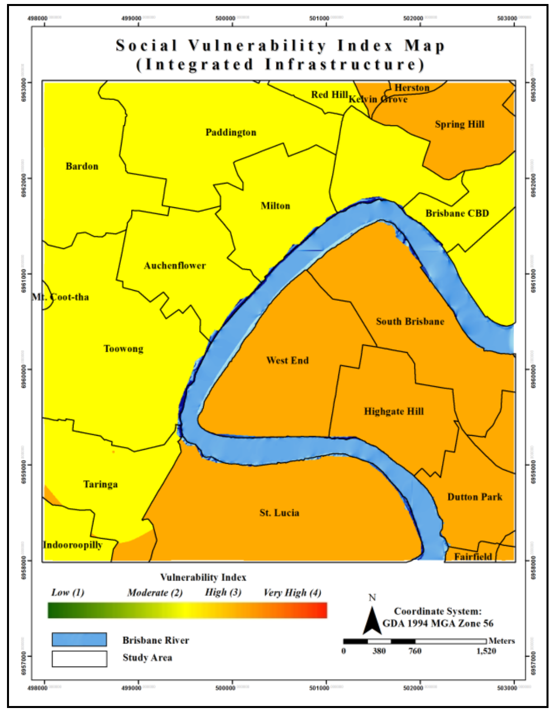


Figure 4.24 The weighted social vulnerability index map for assessing the integrated infrastructures

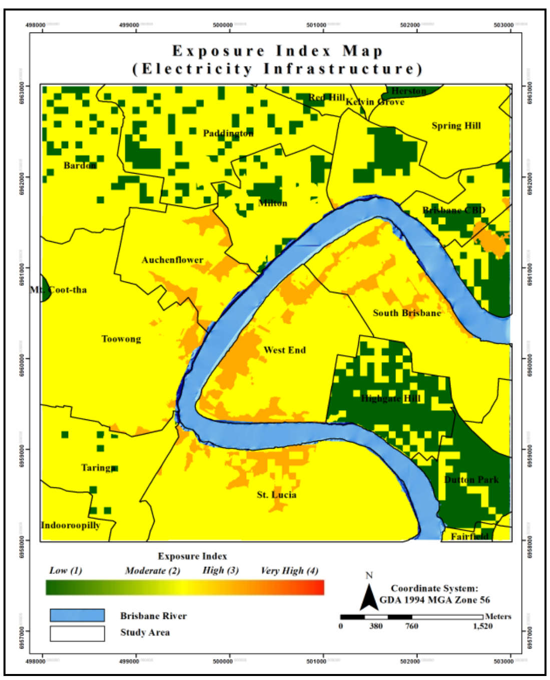


Figure 4.25 The weighted exposure index map for assessing electricity infrastructure

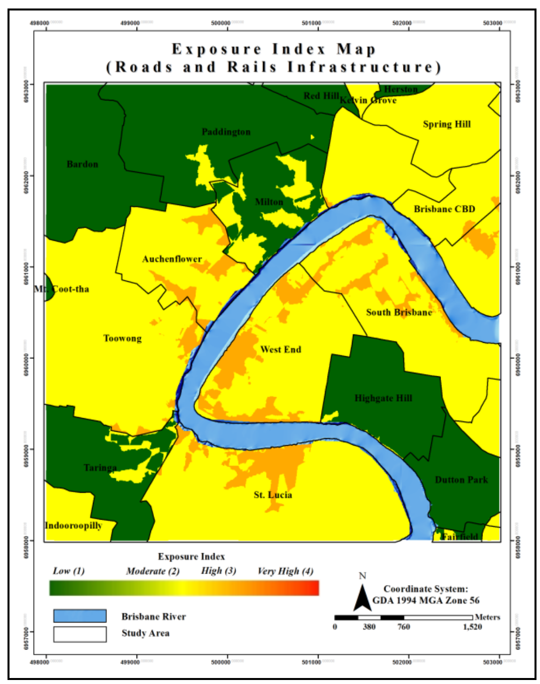


Figure 4.26 The weighted exposure index map for assessing road and rail infrastructures

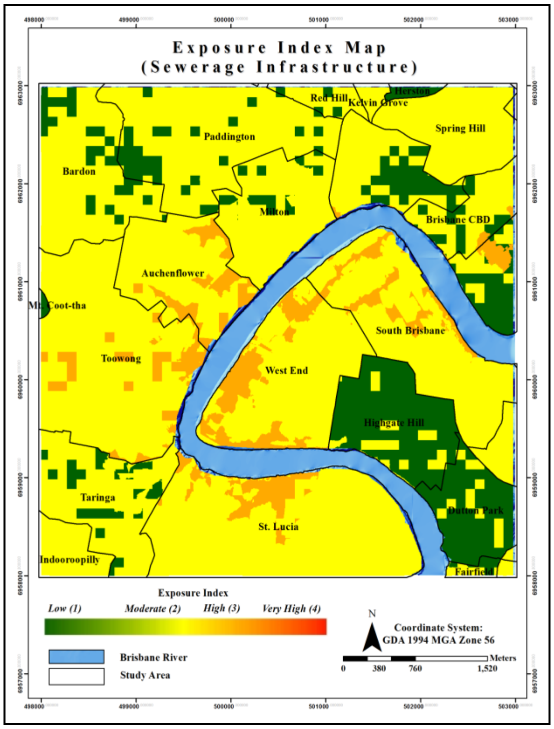


Figure 4.27 The weighted exposure index map for assessing sewerage infrastructure

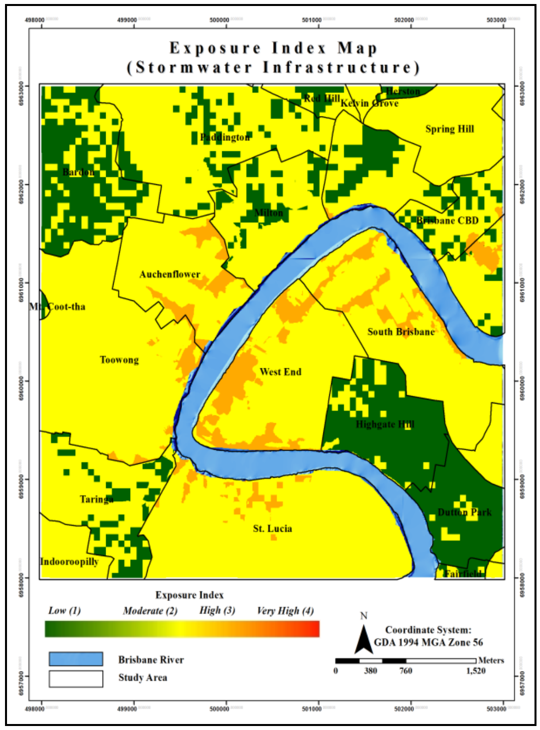


Figure 4.28 The weighted exposure index map for assessing stormwater infrastructure

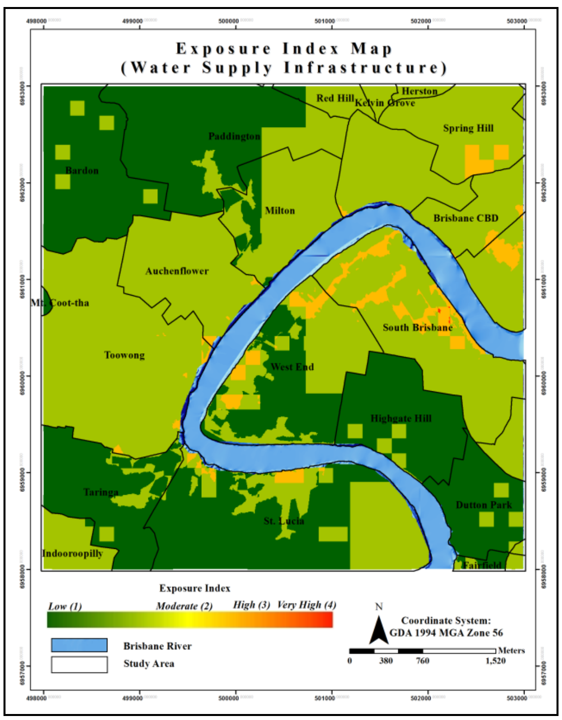


Figure 4.29 The weighted exposure index map for assessing water supply infrastructure

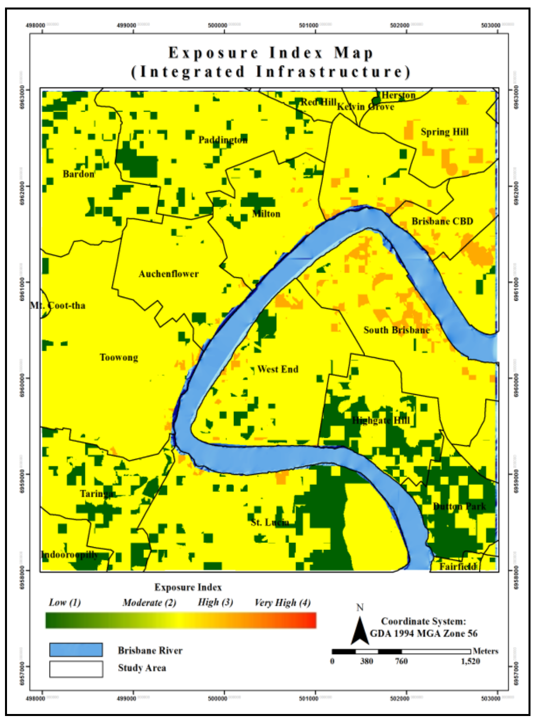


Figure 4.30 The weighted exposure index map for assessing the integrated infrastructures

In conjunction with the fuzzy gamma overlay analysis (see Chapter 3), Equations 3.1 to 3.6 were operationalised to calculate the flood risk and climate adaptation capacity indices. As explained in Chapter 3, the fuzzy gamma overlay operation was chosen in this study to resolve the confusion as to which risk equation (see Eq. 3.1 and 3.2) will be used in the assessment. This operation combined the “increasive” and “decreasive” effects of fuzzy “sum” overlay and fuzzy “product” overlay operations, respectively (Farrell *et al.* 2006). Aside from the use of gamma coefficient as a well-known rank correlation measure to quantify the strength of dependence between two variables (Ruiz and Hullermeier 2012), the application of fuzzy gamma model is very useful in analysing the spatial change such as drought hazard which is significant for drought management (Xing-peng *et al.* 2013). Applying 0.9 as the gamma coefficient (ESRI 2011), the overlay operation was made by using the weighted index maps shown in Figures 4.12 to 4.30 by specific infrastructure and then the integrated infrastructure. Using the raster calculator tool in ArcGIS 10, the following flood risk and climate adaptation capacity index maps were generated.

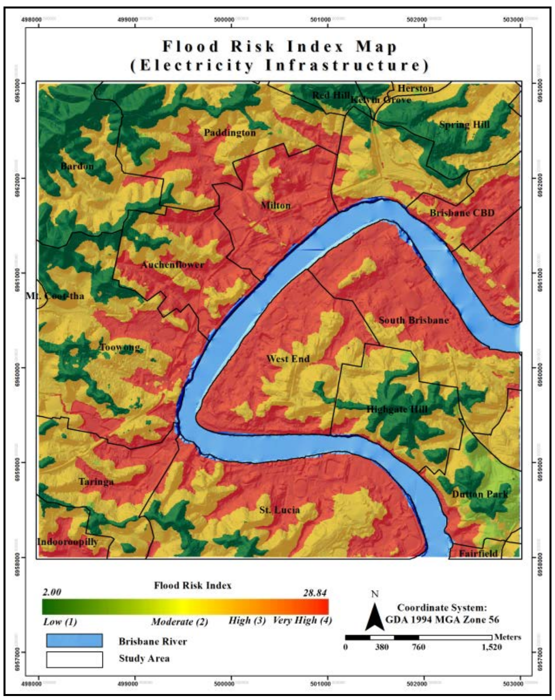


Figure 4.31 The flood risk index map for assessing electricity infrastructure

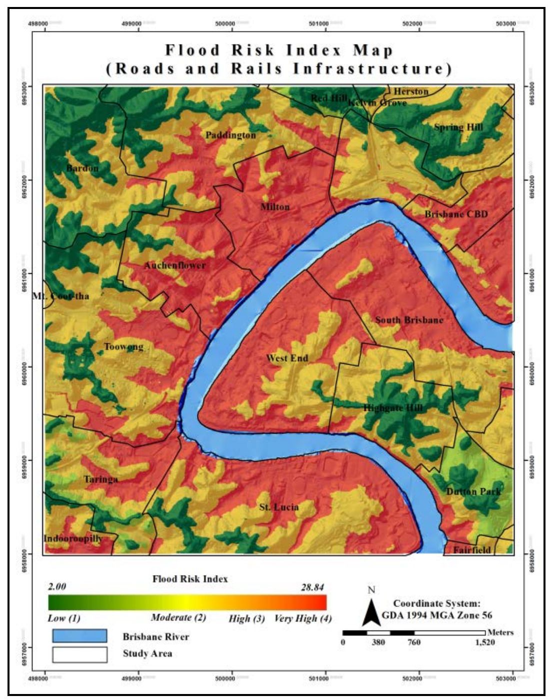


Figure 4.32 The flood risk index map for assessing road and rail infrastructures

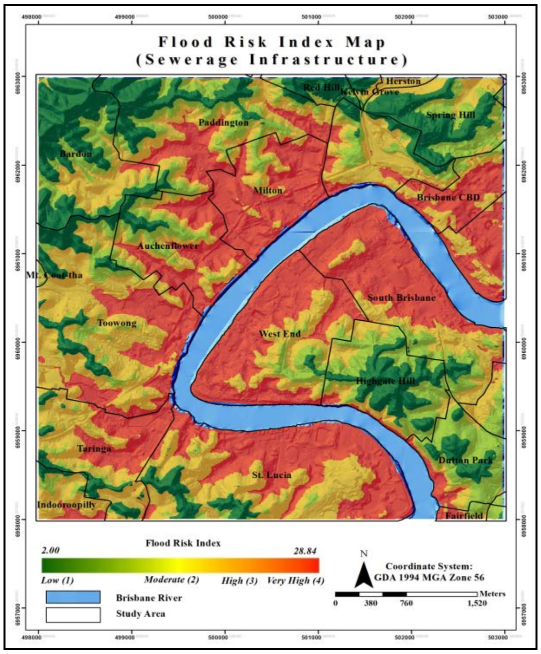


Figure 4.33 The flood risk index map for assessing sewerage infrastructure

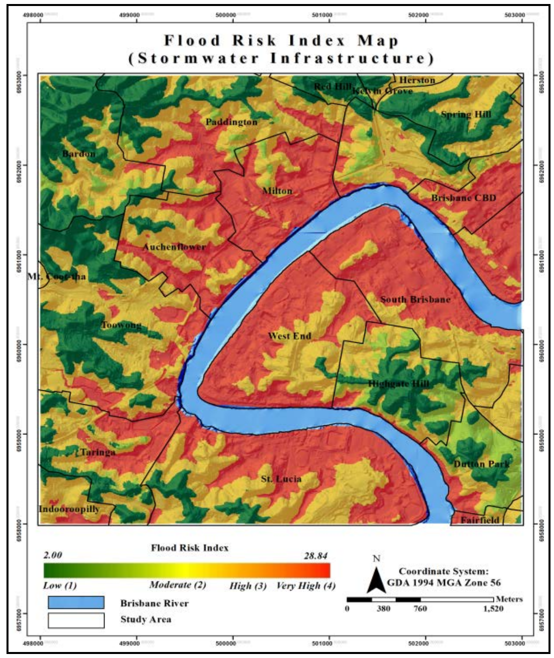


Figure 4.34 The flood risk index map for assessing stormwater infrastructure

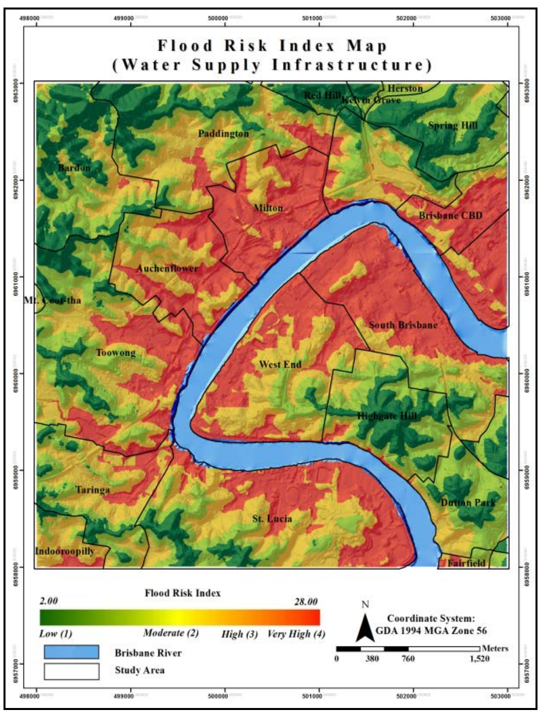


Figure 4.35 The flood risk index map for assessing water supply infrastructure

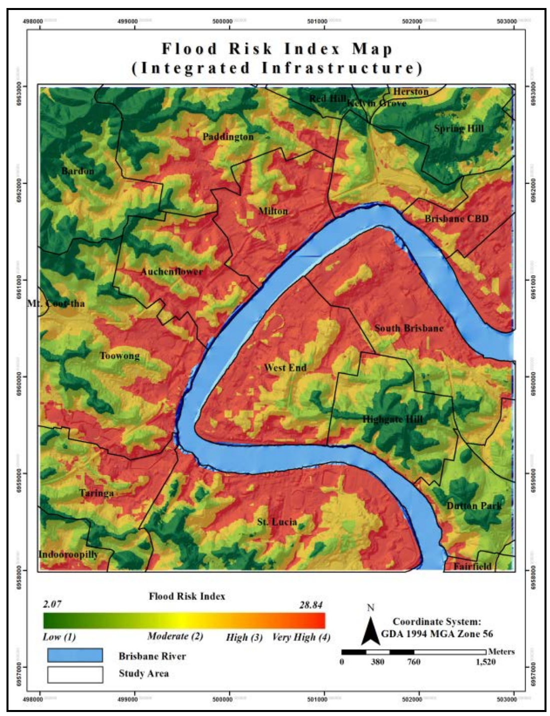


Figure 4.36 The flood risk index map for assessing the integrated infrastructures

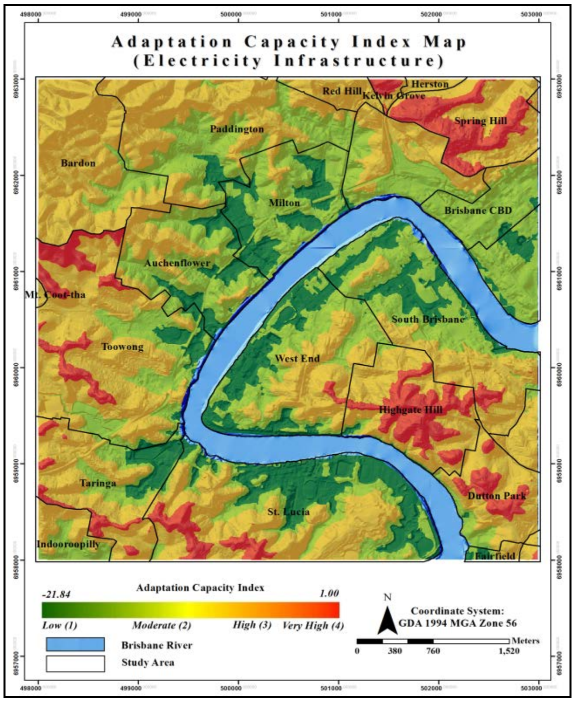


Figure 4.37 The adaptation capacity index map for assessing electricity infrastructure

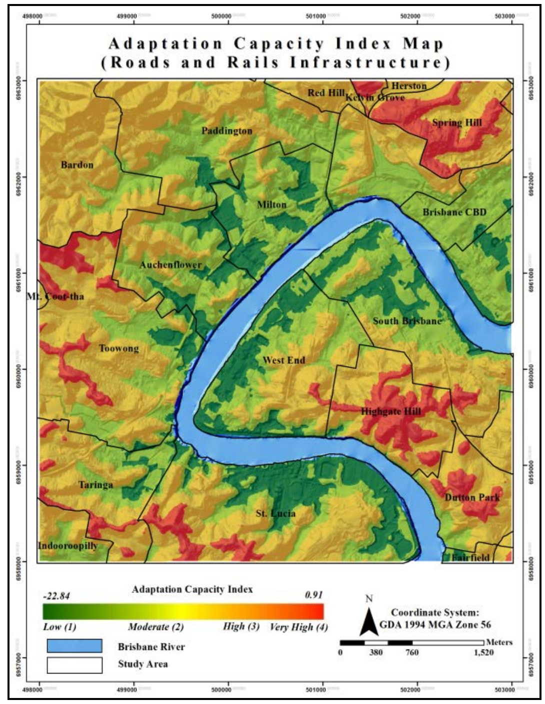


Figure 4.38 The adaptation capacity index map for assessing road and rail infrastructures

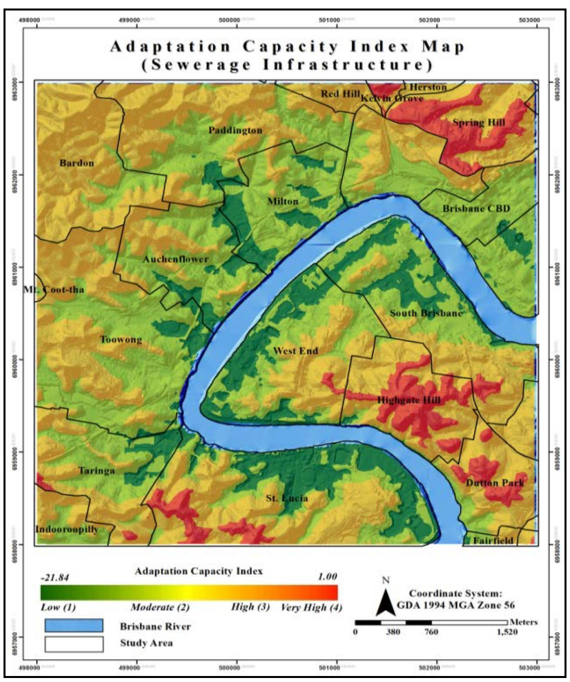


Figure 4.39 The adaptation capacity index map for assessing sewerage infrastructure

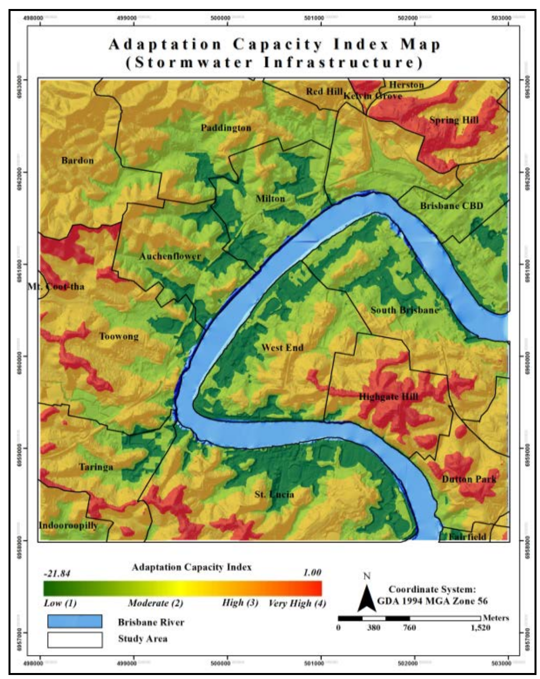


Figure 4.40 The adaptation capacity index map for assessing stormwater infrastructure

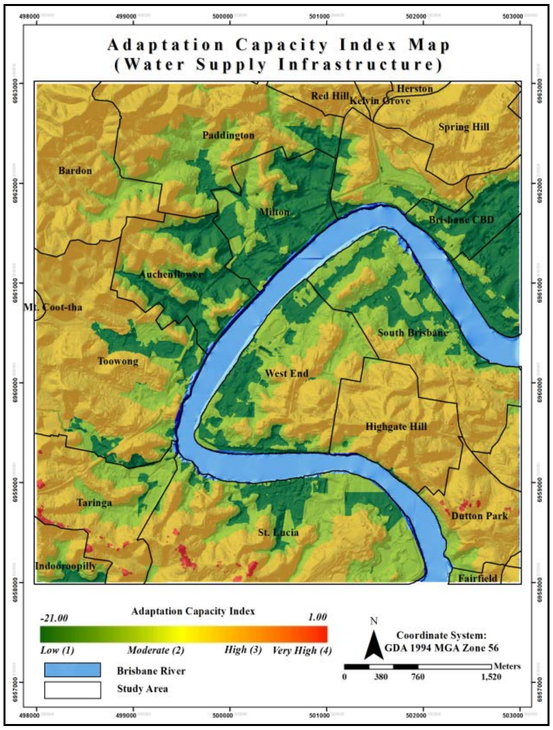


Figure 4.41 The adaptation capacity index map for assessing water supply infrastructure

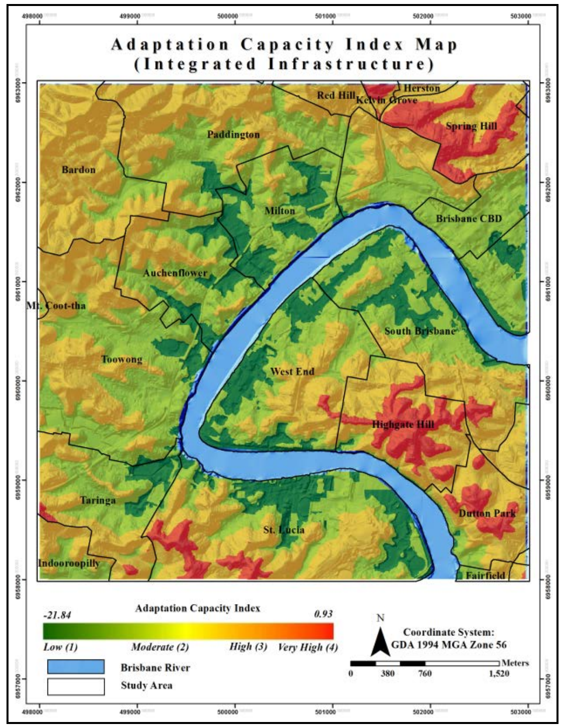


Figure 4.42 The adaptation capacity index map for assessing the integrated infrastructures

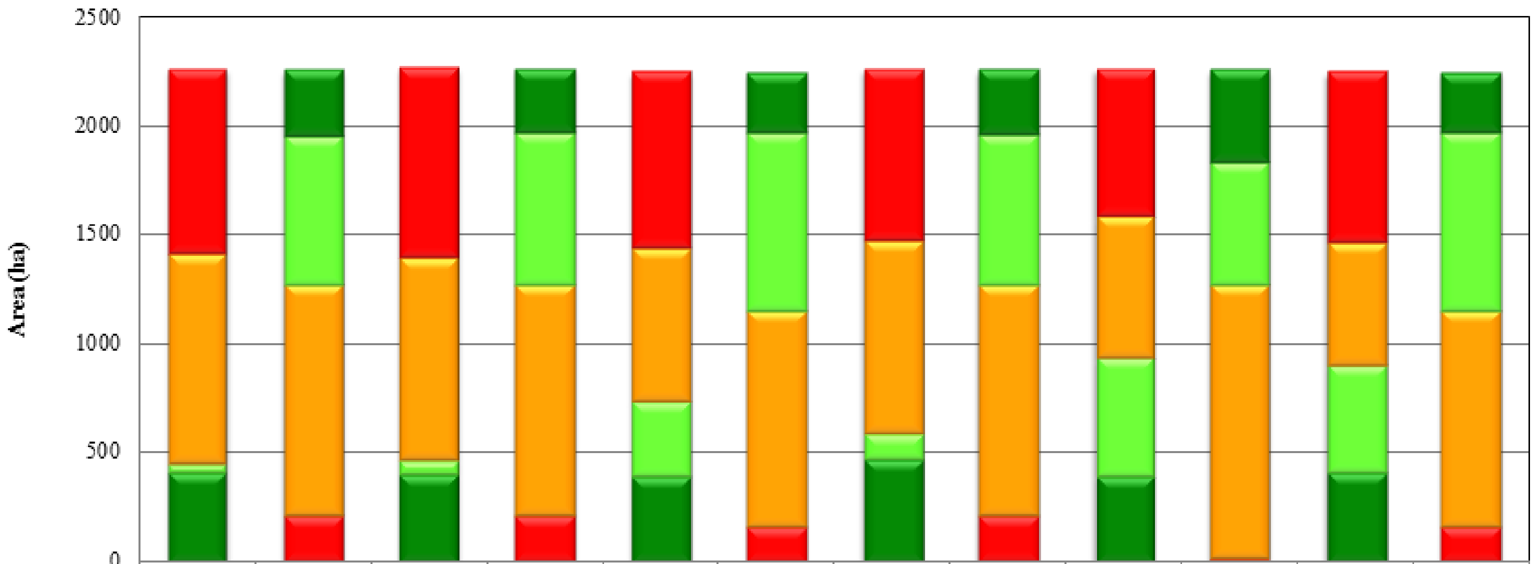
Figure 4.43 below summarises Figures 4.31 to 4.42 in stacked columns which compare the contribution of each area (in hectares) being occupied by the level of flood risk and adaptation capacity to the total study area across infrastructure categories. The colour-coded vertical rectangles show the four levels of flood risk and adaptation capacity with dark green, light green, orange, and red as low, moderate, high, and very high, respectively. The bar graphs also show the inverse relationship of flood risk and adaptation capacity by infrastructure category. By comparing the red columns (i.e. very high) from the flood risk as against the dark green columns (i.e. low) from adaptation capacity, the analysis revealed that the areas being occupied with very high flood risk are larger than the areas being occupied with low adaptation capacity across infrastructure categories. The same observation was also demonstrated when the infrastructures were integrated.

Furthermore, this inverse relationship of flood risk and adaptation capacity signifies that areas of low adaptation capacity are located on areas of very high flood risk.
On the other hand, when dark green columns (i.e. low) from flood risk were compared as against the red columns (i.e. very high) from adaptation capacity, the analysis revealed that the areas being occupied by very high adaptation capacity are smaller than the areas being occupied by low flood risk all across infrastructure categories. This trend was further exemplified when these infrastructures were integrated.

The significance of understanding this relationship demonstrates that flood risk outweighs the climate adaptation capacity of the study area. The fine points are discussed in the succeeding section.

4.3.3 Flood Risk and Climate Adaptation Capacity Model Applications

Figures 4.31 to 4.42 are also summarised in Table 4.3 below. This matrix shows the proportional values of areas being occupied by flood risk (in yellow rows) and climate adaptation capacity (in green rows) with corresponding metrics by descriptive level across infrastructure category. In conjunction with the fuzzy gamma overlay analysis (see Chapter 2), the metrics were calculated using Equations 3.1 to 3.6 described in Chapter 3 through the raster calculation technique in ArcGIS 10.



Legend	Electricity: Flood Risk	Electricity: Adaptation Capacity	Roads & Rails: Flood Risk	Roads & Rails: Adaptation Capacity	Sewerage: Flood Risk	Sewerage: Adaptation Capacity	Stormwater: Flood Risk	Stormwater: Adaptation Capacity	Water Supply: Flood Risk	Water Supply: Adaptation Capacity	Integrated Infrastructure: Flood Risk	Integrated Infrastructure: Adaptation Capacity
Very High	848	304	871	294	808	278	794	301	682	426	781	276
High	957	689	927	701	707	821	881	692	649	567	568	823
Moderate	43	1064	68	1067	341	992	113	1064	540	1260	484	992
Low	415	206	402	206	393	157	475	206	393	10	416	157

Figure 4.43 The area coverage of flood risk and climate adaptation capacity by infrastructure asset

Table 4.3 The area coverage (%) and corresponding flood risk and adaptation capacity metrics

Level	Low		Moderate		High		Very High	
Scale / Infrastructure	Area (%)	Metric/ Index	Area (%)	Metric/ Index	Area (%)	Metric/ Index	Area (%)	Metric/ Index
Electricity	18	2.00-3.95	2	3.95-4.12	42	4.12-6.06	38	6.06-28.84
	13	-21.84- -3.26	30	-3.26- -1.24	47	-1.24- 0.00	9	0.00-1.00
Roads & Rails	18	2.00- 3.95	3	3.95 - 4.12	41	4.12 – 6.06	38	6.06 – 28.84
	13	-22.84- -3.30	31	-3.30- -1.31	47	-1.31- 0.00	9	0.00-0.91
Sewerage	17	2.00-3.95	15	3.95-4.12	31	4.12-6.06	37	6.06-28.84
	12	-21.84- -3.26	37	-3.26- -1.24	44	-1.24- 0.00	7	0.00 – 1.00
Stormwater	21	2.00-3.95	5	3.95-4.12	39	4.12-6.06	35	6.06-28.84
	13	-21.84- -3.26	31	-3.26- -1.24	47	-1.24-0.00	9	0.00-1.00
Water Supply	17	2.0-4.90	24	4.90-5.33	29	5.33-8.23	30	8.23-28.0
	19	-21.00- -4.80	25	-4.80- -2.12	56	-2.12-0.00	0	0.00-1.00
Integrated Infrastructure	18	2.07-4.02	22	4.02-4.18	25	4.18-6.12	35	6.12-28.84
	12	-21.84- -3.32	37	-3.32- -1.30	44	-1.30-0.00	7	0.00-0.93
Average	18		12		34		36	
	14		32		47		7	
DRR Measures/ CA Strategies	Mitigation		Mitigation to Preparedness		Mitigation to Response		Mitigation to Recovery	

Flood risk
Climate adaptation capacity

Interestingly, Table 4.3 shows the relationship between the climate adaptation capacity metrics (in green rows) and the flood risk metrics (in yellow rows) of the study area. Analysing the matrix by column, for example, it shows that the percentage of areas occupying very high level of flood risk is larger than the percentage of areas being occupied by very high adaptation capacity. On the average, seven percent (7%) of the study area (approximately 158 ha) reveal positive adaptation capacity metrics (>0 to maximum of 1). This positive adaptation capacity metrics would signify that the resources within those areas are one unit above the zero break-even and would indicate a positive measure of the capability to mitigate flood or climate risk. However, extra caution should be taken into account considering that some areas are positioned in a highly favourable physical condition (e.g. higher elevation) but the socio-economic resources inhibit the adaptation to climate risk.

Moreover, the majority of the study area (93%) reveals negative adaptation capacity metrics (minimum of -22.84 to <0) which indicate that the capacity of the urban community requires further deliberation as to how climate adaptation is intrinsically inseparable to the physical and social vulnerability. If vulnerability takes the definition in this study as the capacity of the people, community, or system to withstand flood risk, it follows then that vulnerability is inherently associated with the general political-economy of resources, wealth, physical and social well-being, governance, and political will. This significant finding would imply that vulnerability as a resource-oriented factor determines the strength or weakness of the study area; such that the generated negative values for adaptation capacity meant that the resources (e.g. socio-economic) are not enough to increase climate resiliency of the urban community and critical infrastructures (Espada *et al.* 2012). The results further signify that the resources of the community are outbalanced by 31 units taking zero as the break-even metric.

Consistent with the DOTARS'(2002) findings, the response measures on floods, coastal inundation, storms and cyclones are not sufficient to assist the economic and social recovery of the communities. In 2013, the Commonwealth government of Australia had planned to set up the National Insurance Affordability Council, which would manage the $500 million worth of national co-ordination of flood-risk management and other natural disaster mitigation projects (Hannam 2013). However, the cost of the entire expense for the projects was yet unclear (Hannam 2013). Hence, this study emphasised the importance of linking the flood risk and adaptation capacity metrics to identify flood priority areas for funding support to increase climate resiliency.

These findings would further imply that the study area requires a range of disaster risk reduction (DRR) or climate adaptation (CA) adaptation strategies that would increase community and critical infrastructure resiliency. Adopted from Queensland Reconstruction Authority's (QRA) (2011) four phases of disaster risk reduction, the broad adaptation strategies identified to increase community resiliency include mitigation, preparedness, response, and recovery. Looking back at Table 4.3, the matrix suggests of considering the following disaster risk reduction measures and/or climate adaptation strategies:

- Mitigation on areas of low flood risk or very high climate adaptation capacity;
- Mitigation to preparedness on areas of moderate flood risk and high climate adaptation capacity;
- Mitigation to response on areas of high flood risk and moderate climate adaptation capacity; and
- Mitigation to recovery on areas of very high flood risk and low climate adaptation capacity.

The specific discussions on this area of research are outlined in Chapters 5 and 6.

4.4 Summary and Conclusion

This Chapter discussed the novel approach of integrating the flood risk and climate adaptation capacity assessment process. This includes the linkage application of Artificial Neural Network (ANN), Bayesian joint conditional probability, weighted overlay, and fuzzy gamma overlay within the GIS framework. A better understanding was gained about the process of integrating the flood risk and climate adaptation capacity indicating variables using those analytical tools. This has been demonstrated by the improved method of assessment such as: 1) the empirical selection of flood risk and climate adaptation capacity indicating variables through the application of Self-Organizing Neural Network (SONN); 2) the application of Bayesian joint conditional probability in assigning weights of indicating variables rather than using equal weighting and expert opinion; and 3) the operation fuzzy gamma-enabled quantification of flood risk and climate adaptation capacity. This will offer reduction in computational confusion, uncertainty on data selection and assigning of appropriate probable weights, and the time and resources involved in the climate risk analysis. Significantly, the procedures used in this study comprehensively discussed the mapping of flood risk (i.e. descriptive modelling) and extended to climate adaptation strategies (i.e. prescriptive modelling) within the GIS environment.

Identified as the main contribution in this study, i.e. the *flood risk-adaptation capacity index-adaptation strategies (FRACIAS) linkage model*, the model allows the identification of areas characterised with very high flood risk and low adaptation capacity. The model was further used in identifying the disaster risk reduction measures and climate adaptation strategies in the study area. The results from this study are particularly useful for the development of sustainable policies on natural disaster risk reduction, identification of priority communities for building climate resiliency, and systematic integration of mitigation, preparedness, response, and recovery programs in the reconstruction of communities exposed to climate risk.

Whilst the flood risk and adaptation capacity indices were obtained through a robust methodology, the disaster risk reduction measures and adaptation strategies were identified subjectively – an issue that is further addressed in Chapter 6 through an optimisation technique called Markov Decision Processes (MDPs).

Chapter 5

VULNERABILITY ASSESSMENT OF CRITICAL INFRASTRUCTURES FOR INTERDEPENDENCY ANALYSIS

5.1 Introduction

This Chapter provides innovative contribution in the utilisation of GIS in assessing the vulnerabilities and characterising the interdependencies of critical infrastructure systems (CIS). As a significant issue for exploration, this study examined the vulnerabilities and interdependencies of electricity, roads and rails, sewerage, stormwater, and water supply into three (3) aspects: (1) network modelling of CIS vulnerabilities; (2) characterising the CIS interdependencies; and (3) outlining the climate resiliency measures for flood mitigation and climate adaptation.

Applying the utility network theory, the development of this analytical tool aimed to assist infrastructure managers in the preparation of contingency plans and operations particularly during extreme climatic event such as flooding. By showing the infrastructure networks' potential path of disruption due to flooding, this research innovation allows planners and responders to visually identify interrupted networks in order to make informed decisions for efficient disaster risk reduction and climate adaptation.

Whilst catchment and land use management considered the significance of an integrated approach in floodplain management, the interdependency of critical infrastructures is often neglected in formulating the climate adaptation strategies and flood disaster risk reduction measures. Finding and learning the adaptation measures implemented during the 2010/2011 floods in Queensland will contribute in the improvement of infrastructure interdependency management within other flood plains.
The research issues and justifications on the choice of analytical tools used in this Chapter are discussed in the subsequent sections and more in Chapter 2 (Literature Review).

5.2 Research Methods

5.2.1 Setting the Dimensions of Critical Infrastructure Interdependency

The dimensions of critical infrastructure interdependency in Queensland in relation to the 2010/2011 flood events are conceptualised in Figure 5.1. This study investigated the interrelated factors influencing the dimensions of infrastructure interdependency namely, a) climate risk environment, b) infrastructures' cascade and common cause failures, c) adaptation/resiliency measures, and d) physical and geographic types of interdependency.

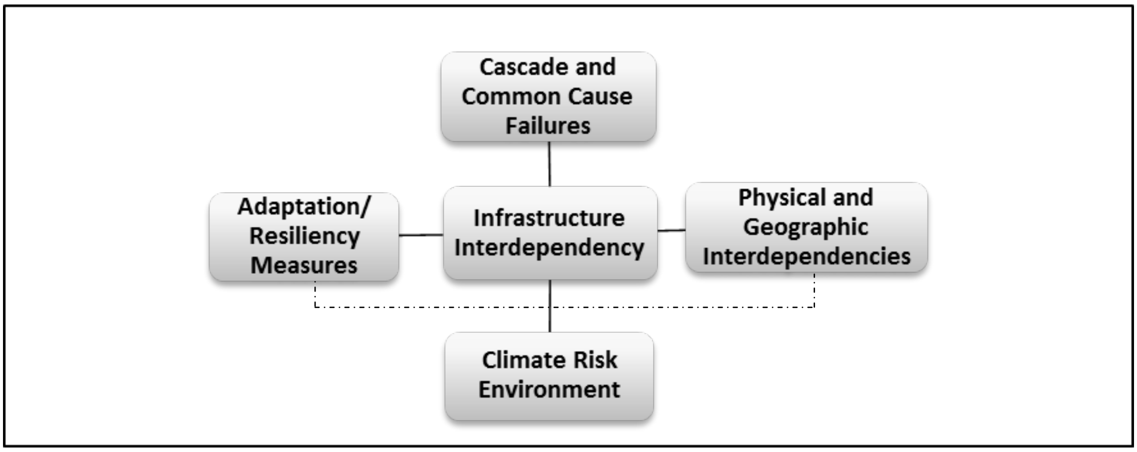


Figure 5.1 The dimensions of infrastructure interdependency used in this study (adopted from Rinaldi *et al.* 2001)

5.2.2 Climate Risk Environment

Floodplain risk management refers to all courses of actions that enable a floodplain ecosystem manage and cope with floods (NFRAG 2008). In Australia, the floodplain ecosystems are areas of commercial, social, and ecological significance where towns and cities were principally located due to historical reasons associated with access to fertile soil, water supply, recreation, etc. (QRA 2011). These towns and cities are dependent on critical infrastructures to function effectively. Ideally, these critical infrastructures should be built outside flood prone areas; however, many of the infrastructures such as electricity, telecommunications and sewerage did not exist during the early period of town and land use planning.

Floodplains are highly productive ecosystems, but intensively used by humans for agricultural and urban development, which in turn resulting in the loss of biodiversity and ecological functioning (Tockner *et al.* 2008). When massive floods occur across inhabited floodplain areas, it can result in significant damages to public infrastructures, private properties, and economy. These consequential damages of floods can cause the loss of lives, disrupt significant infrastructure services, and bring enormous challenges for immediate socio-economic recovery.

One way to conceive disaster risk reduction (DRR) initiatives is to understand the four (4) interrelated steps: acknowledge risk, assess (characterise and analyse) risk, communicate risk, and address risk (Bell 2010). Risk assessment and addressing the risk offer the greatest challenge in disaster risk reduction. Floodplain disaster risk assessment requires accurate information and an in-depth understanding of the three components of risk: hazard, vulnerability and exposure. Specific considerations in the assessment include the determination of the nature and extent of risk by analysing potential hazards and evaluating existing conditions of vulnerability that together could potentially harm exposed people, property, services, livelihoods and the environment on which they depend (UNISDR 2009). The flood risk and climate adaptation capacity assessments were initiated to help address this issue. The procedures and discussions were comprehensively set in Chapters 3 and 4.

In linking Chapters 3 and 4 in setting the climate risk environment, those chapter studies were conducted to assess the flood risk and climate adaptation capacity of the study area. The process started with the standardisation and transformation of thirty seven (37) flood risk and climate adaptation capacity indicating variables (5 for hazard, 7 for physical vulnerability, 17 for social vulnerability, and 8 for exposure) with different spatially-explicit analytical tools such as a) high resolution digital elevation modelling and urban morphological characterisation with 3D analysis, b) spatial analysis with fuzzy logic, c) geospatial autocorrelation techniques with global Moran's I and Anselin Local Moran's I, among others. Using a 2-dimension self-organising neural network (SONN) with 100 neurons and trained by 200 epochs, the standardised variables were selected for inclusion in the Bayesian joint conditional probability weighted overlay and modified fuzzy gamma overlay operations. There were two outputs generated from the analyses: the flood risk model and the climate adaptation capacity model. The outputs of the overlay analyses revealed an inverse relationship between the degree of flood risk and climate adaptation capacity (Espada *et al.* 2013b, 2013c). Being readily available, the flood risk map generated from these previous studies was used to set the climate risk environment.

The complex nature of the climate risk environment significantly poses challenges in understanding interdependency. Climate risk, either in the form of climate change or variability, is one of the biggest challenges the world faces. The extreme weather events in December 2010 to January 2011 that resulted in a series of damaging floods in the State of Queensland, Australia (McDougall 2012) are good examples. Hence, it is important to build a strong flood risk management scheme to achieve a highly adaptive and resilient State and its infrastructures. However, flood plain planning schemes often lack the consideration of an interdependency approach.

5.2.3 Critical Infrastructures' Common Cause and Cascade Failures

No matter how any government and public intensify its willingness to pay for resilience, failures cannot be avoided (Collins *et al.* 2011). However, a proactive approach of risk management can help minimise the problem rather than to wait for infrastructure failures and breakdowns due to its inherent vulnerabilities (Johansson and Hassel 2010). Otherwise, failures may cascade from one infrastructure system to another (Little 2002) or even get back to the system itself due to high degrees of complexity (Johansson and Hassel 2010), spatial dependencies and interdependencies (Zimmerman 2001).

This section probes the failures of the critical infrastructures through risk and/or vulnerability assessment into two levels: the single system level and multi-system level. As a good basis for decisions regarding disaster risk reduction (Aven 2003) and climate adaptation, risk and vulnerability assessment will increase our knowledge about how the critical infrastructures in Brisbane City were exposed to flood hazards and what were the consequences that aroused from the exposure.

5.2.3.1 Modelling the Individual Systems

The approach to critical infrastructure vulnerability assessment in this study was motivated by the field of network theory where two basic components, nodes and edges, build up the model of the system (Johansson and Hassel 2010). A network is

a set of interconnected line features that represent paths of movement (Davis 2001) within which characterised by edges and nodes or junctions. The edge is the line that runs between two nodes or junctions (Mitchell 2012). A node is not a physical “point”, but only a location indicator for the beginning and end of the edge (Davis 2001). At the single system level, this study used the network theory because, aside from measuring topological interconnection as emphasised in Chapter 2, it serves as a screening tool for identifying the most vulnerable parts of a critical infrastructure (Eusgeld *et al.* 2009). In ArcGIS 10, two nodes are required to be clearly defined in order to execute the network model: the source and the sink. The source is the beginning node while the sink is the end node.
In this study, the structure of the network models was guided by the following procedures:

1. Identification of feature classes to participate in the network.
2. Creating the network connectivity rules that constrain the type of infrastructure network assets that allow to be connected to each other. The Utility Network tool of ArcGIS 10 was operationalised in establishing the network connectivity rules.
3. Using the generated flood risk and/or climate adaptation capacity map of individual infrastructure from Chapter 4 to geographically locate either the sources or the sinks of the infrastructure network within areas of very high flood risk and low adaptation capacity.

5.2.4 Characterising the Critical Infrastructure Interdependencies

Comprehensively discussed above are issues and methods associated with the fundamental understanding of the risk and vulnerabilities of critical infrastructures at the single level. Whether these critical infrastructures are state-owned or managed by local councils, their risk assessment approaches vary according to their requirements. There is no single entity attempts to integrate these infrastructures to evaluate and assess the risk of the critical infrastructures at the system-of-systems level. Hence, this section is designed to look at the infrastructure system at a larger and comprehensive scale. Following the argument of Burian *et al.* (2013), the goal of this study was not mainly to summarise the climate vulnerabilities and adaptation strategies of infrastructure systems but also to highlight the importance of the interdependency of infrastructures in relation to extreme climatic event.

A variety of analytical tools (e.g. Supervisory Control and Data Acquisition (SCADA)) is currently available in understanding the behaviour of critical infrastructures either at single system level or interdependency level. This section focuses on the interdependency approach of assessing the risk and vulnerabilities of critical infrastructures. The relational interdependencies of critical infrastructures were analysed using the Identity Analysis and Query Builder tools in ArcGIS 10. The former computed the intersections of all vulnerable infrastructures with identity values shown in Table 5.1. On the other hand, query builder were used in ArcGIS 10 to select the identity of the critical infrastructures specified in Table 5.1 to set the geographic interdependency of the critical infrastructures. An example is shown in Figure 5.2.

Table 5.1 The identity values of critical infrastructures

Critical Infrastructure	Identity
Electricity Network	1
Road Network	2
Railway	3
Water Supply Network	4
Stormwater Network	5
Sewerage Network	6

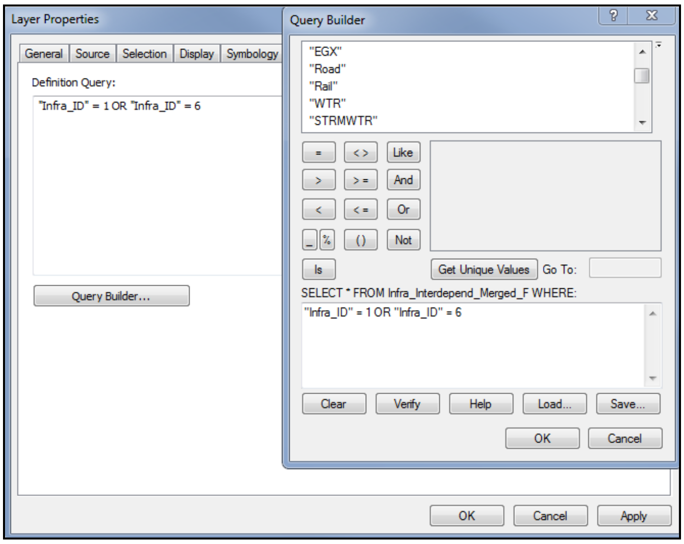


Figure 5.2 A sample query builder used to identify the geographic interdependency of electricity and sewerage networks

5.3 Results and Discussions

5.3.1 Vulnerability Assessment of Critical Infrastructures at Single System Level

The vulnerability of critical infrastructures at single system level is discussed in this section. The infrastructures included in the analysis were electricity, road and rail, water supply, sewerage, and stormwater networks.

5.3.1.1 Electricity Network Model

Power outages during the 2010/2011 floods in South East Queensland were directly and indirectly linked to flood-damaged network that caused significant consequential effects such as (Energex 2011b):

- Devastation of property
- Major pre-emptive interruption of supply to approximately 150,000 customers in Ipswich and Brisbane areas; and
- Cleaning up and restoration of power to approximately 60,000 homes affected by flood waters.

The distribution of electrical power in Queensland is provided by Energex Limited and Ergon Energy Coporation Limited (QFCI 2011, QFCI 2012). Energex is responsible for the electricity distribution in South East Queensland including the regions of Brisbane, Ipswich, Gympie and the Lockyer Valley (Energex 2011) while Ergon Energy is responsible to rural and regional Queensland (DEWS 2013) as shown in the following maps. The former, a government-owned corporation, provides electricity supply to 1.32 million customers in the region, of which 1.21 million are residential (Energex 2011b).

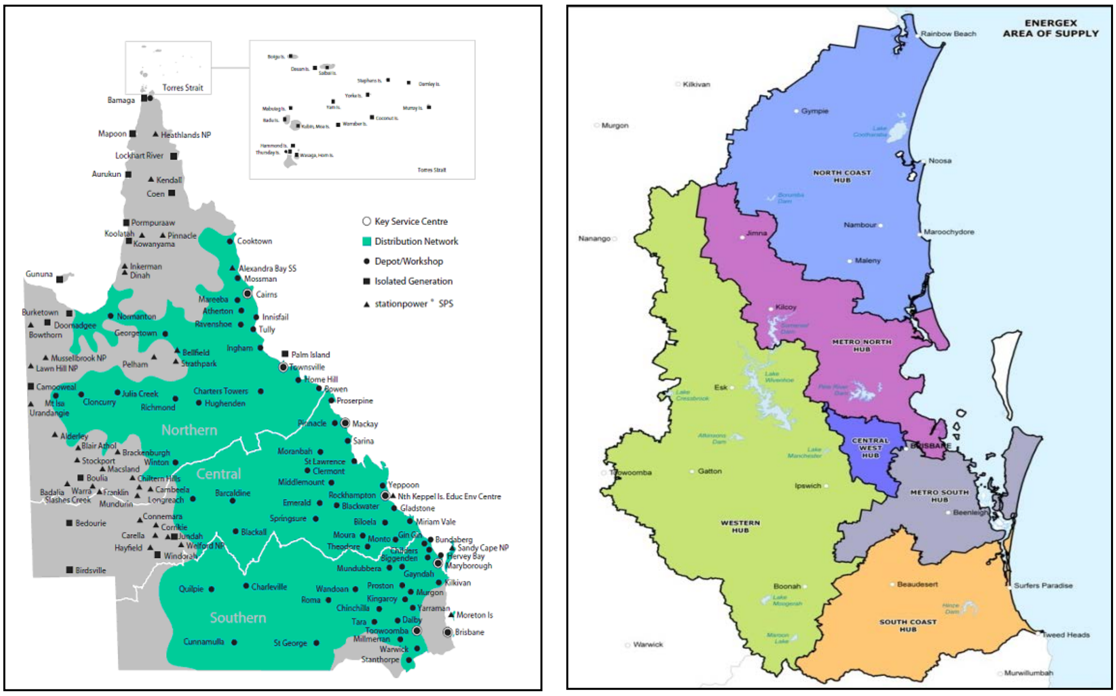


Figure 5.3 The Ergon Energy (left) and Energex (right) power distribution maps (Source: Australian Energy Regulator (AER))

The electricity supply system in Queensland has four interconnected components: generation, transmission, distribution and retail (DEWS 2013) (see Figure 5.3).

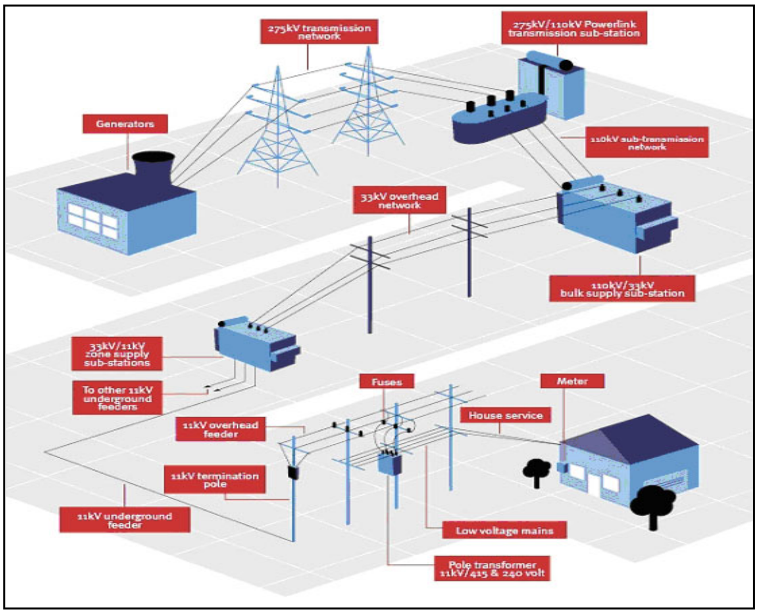


Figure 5.4 The typical electricity supply system in Queensland
(Source: Department of Energy and Water Supply (DEWS))

Electricity generation is the process of producing power at power stations from utilising other sources of primary energy such as coal, gas, oil, water, wind, geothermal or solar (DEWS 2013). In Queensland, electricity generation is provided by government-owned corporations and private companies (DEWS 2013).

Electricity transmission is the transport of high voltage electricity from power stations where electricity is generated to the electricity distribution networks (Powerlink Queensland 2012). In Queensland, Powerlink transmits high voltage in bulk from where it is generated to distribution companies owned by Ergon and Energex and to some major industrial customers (Powerlink Queensland 2012).

The term distribution is used to describe the supply of power from the zone substations to transformers or customer connection points via designated feeders (Energex 2011). In the process of distribution, the voltage of the electricity is progressively reduced at a series of substations throughout the network until it reaches the final voltage of 240 volts (V) for supply to customers (DEWS 2013).

As specified in the Network Management Plan 2011/2012-2015/16, ENERGEX (2011b) takes supply of electricity from Powerlink and distributes the power through sub-transmission and distribution system to customers throughout the SEQ region. The zone substations and distribution substations convert the voltages to meet customers’ requirements and minimise network losses (Energex 2011b). Within the study area, this type of networking system is schematically represented in Figure 5.5. Using six hub centres as ENERGEX’s distribution areas (Energex 2011b), the study area is within the boundary of Central West Hub and Metro South Hub.
Figure 5.5 also depicts that the study area is typically supplied by 110/33 kV or 110/11 kV substations. The area has also extensive older, meshed 33 kV underground cable networks that supply substations (Energex 2011b). These components characterised the nodes and edges that participated in the risk and/or vulnerability assessment of the electricity network as summarised in Table 5.2.

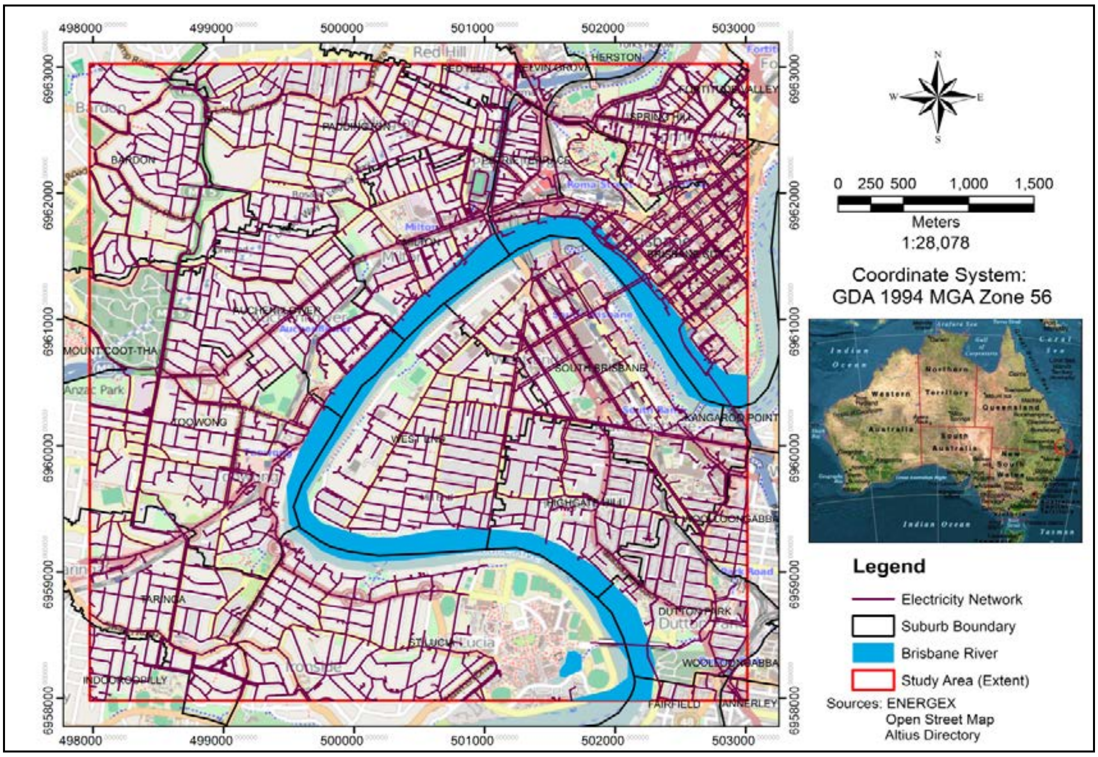


Figure 5.5 The electricity network map of the study area

Table 5.2 The electricity assets that participated in the electricity network model

Source	Edge		Sink
	Transmission Lines	Role	
Zone Supply Substation	110kV	Simple Edge	Underground Sites
	33kV	Simple Edge	Underground Sites
	11kV	Simple Edge	Underground Sites
	Low Voltage	Simple Edge	Overhead Pole Sites
Underground Substation	Low Voltage	Simple Edge	Underground Sites
Underground Cubicle Substation	Low Voltage	Simple Edge	Underground Common Use Sites
Overhead Pole Substation	Low Voltage	Simple Edge	Non-ENERGEX Overhead Sites

After having established the network connectivity rules using the Utility Network tool in ArcGIS 10, the power distribution system was analysed by identifying the highly vulnerable critical assets that were found within areas of very high flood risk and low adaptation capacity (see Chapter 4). The analysis revealed that 75 of these assets are within those areas as summarised in Table 5.3.

Table 5.3 Count of highly vulnerable electricity assets within very high flood risk zone (a) or low adaptation capacity zone (b)

Electricity Asset	North West Area (No.)	South East Area (No.)	Total (No.)
Supply substations	13	0	13
High voltage switches	31	9	40
Pole transformers	11	11	22
Total	**55**	**20**	**75**

Using these highly vulnerable critical electricity assets as flag junctions (see blue, pink and brown dots in Figures 5.6 or 5.7), the connections of electricity transmission lines were traced and then calculated its total linear kilometers. Results of the path analysis revealed that electricity supplies were disrupted along the 627km (75%) and 212km (25%) transmission lines in the North West and South East areas, respectively, due to the flood event. These results are summarised in Table 5.4 with the corresponding vulnerability maps shown in Figures 5.6 and 5.7.

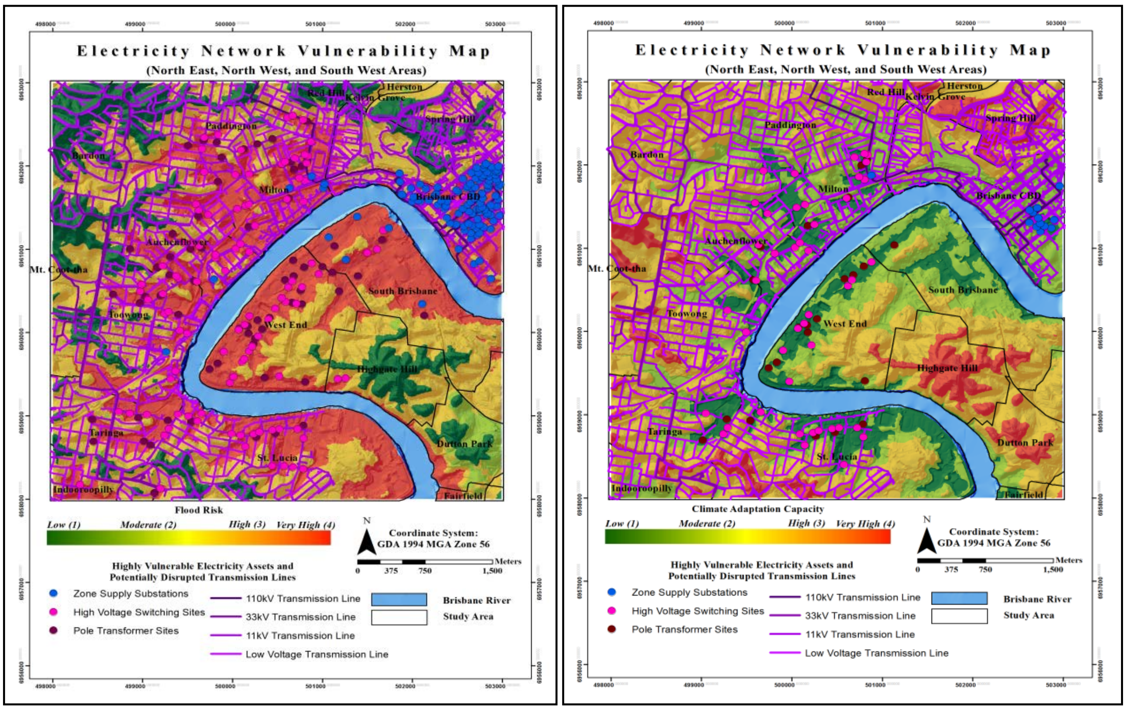


Figure 5.6 The electricity network vulnerability maps in the north east to south west areas using flood risk (left) and climate adaptation capacity (right) models

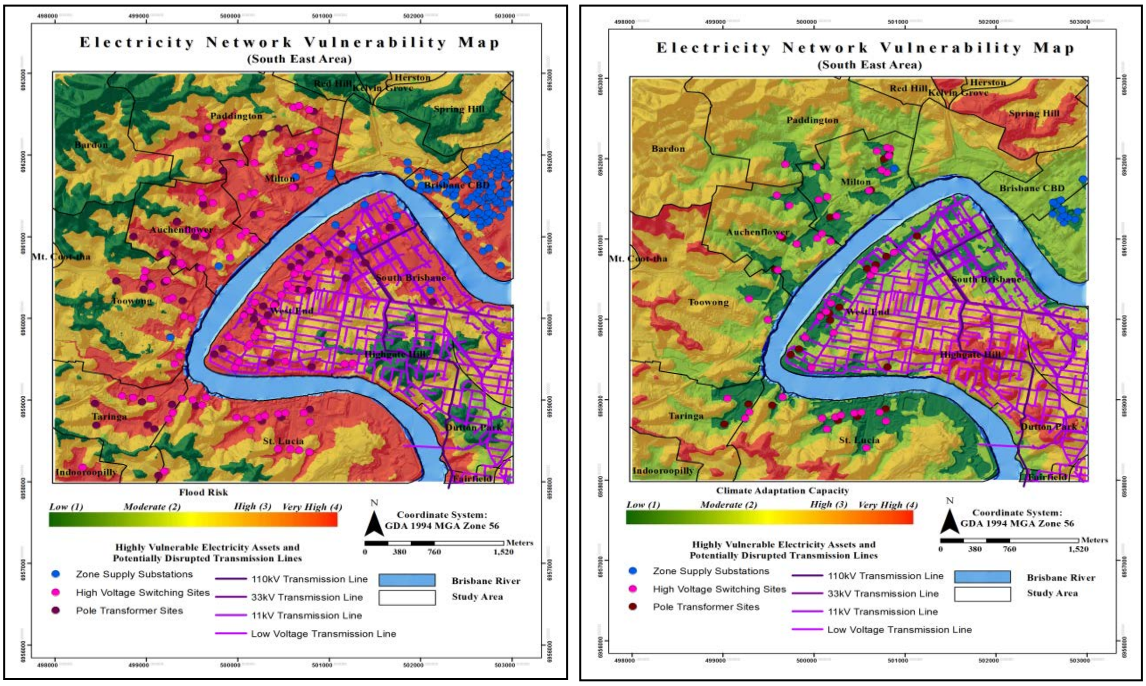


Figure 5.7 The electricity network vulnerability maps in the south east area using flood risk (left) and climate adaptation capacity (right) models

Table 5.4 Summary of potentially disrupted electricity transmission lines within the study area

Transmission Line	Disrupted Connections (linear km)		Total (km)
	North West Area	South East Area	
110 kV	13.80	4.72	18.51
33 kV	22.86	3.90	26.77
11 kV	260.49	81.34	341.83
Low Voltage	330.12	121.82	451.95
Total	**627.27**	**211.78**	**839.06**

As shown in Figures 5.6 and 5.7, the damage to shared electricity network infrastructure due to flooding disrupted the power supply to large numbers of people including non-flooded premises (Arnold 2011, QFCI2012). During the January 2011 flood, power was disconnected in flooded and selected non-flooded areas as precautionary measure. Validated from the QFCI Final Report, one of the highly vulnerable zone substations that was significantly impacted and disconnected during the January 2011 flood that revealed in the vulnerability map was the Milton substation. With the flood reached 0.95m above the 1% annual exceedance probability (AEP) on the site, the floodwaters surrounded the area and significantly damaged the substation's equipment below the flood level with an estimated cost of $750,000 (QFCI 2012).

The results from these analyses can assist power industry to apply vulnerability information in decision-making for increasing critical infrastructure resiliency.

5.3.1.2 Road and Rail Networks

The Queensland's Department of Transport and Main Roads is charged with the development and upkeep of the state-controlled network of roads (QFCI 2012). The state has over 33,000 kilometres of state-controlled roads wherein 9,170 kilometres of these road networks were affected by 2010/2011 flood events with 8,482 kilometres had been recovered as of September 2011 (QRA 2011). One of the implications of the state-wide flooding was the closure of roads, and isolated several rural and urban communities for a number of days.

In Brisbane City, the estimated cost of flood recovery work for minor roads and related infrastructure was $156 million (BCC 2012). The Council restored 91 km of road by September 2011 (BCC 2012b). Figures 5.8 and 5.9 show the road networks within the state of Queensland and the study area, respectively.

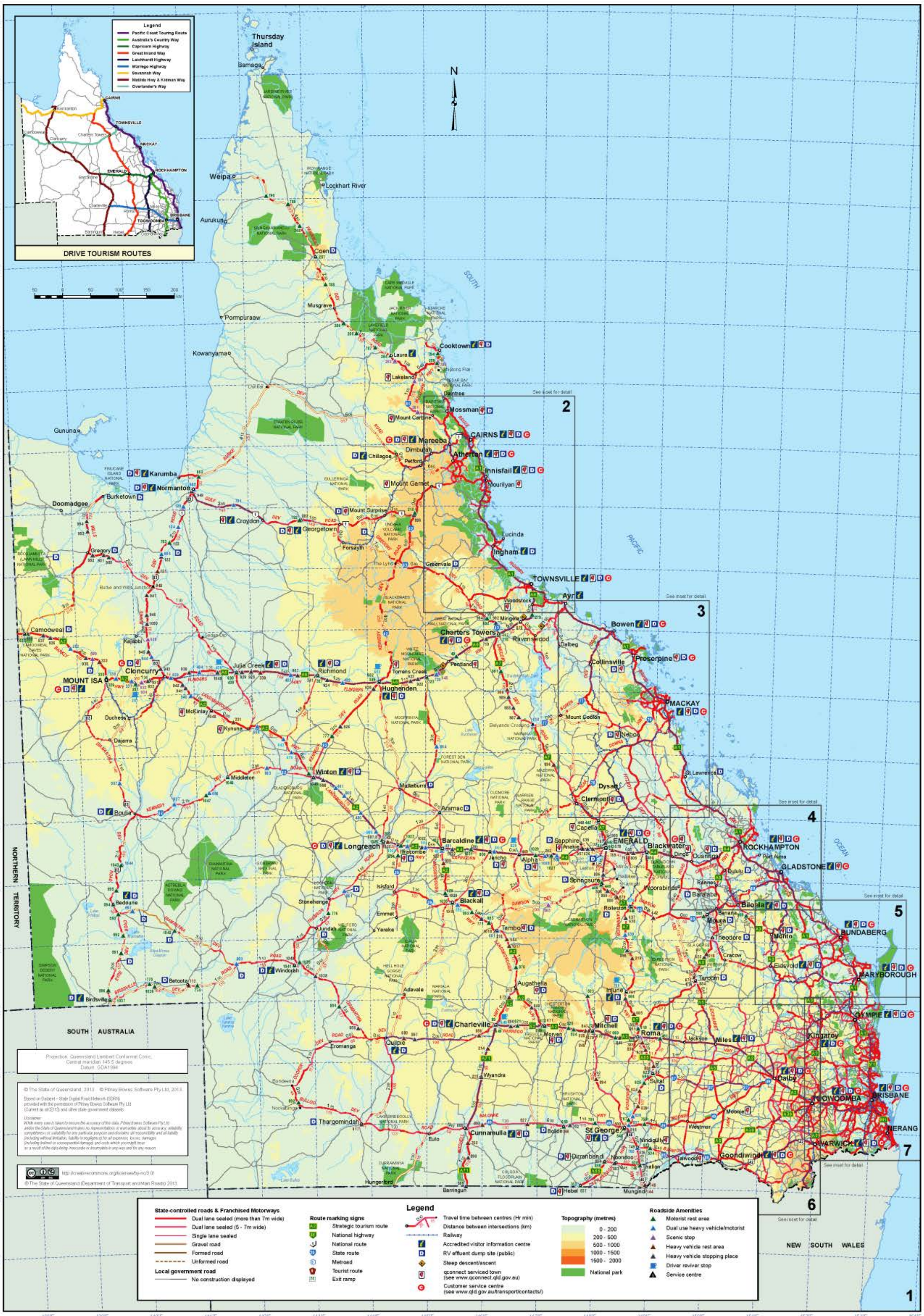


Figure 5.8 The road network map of Queensland
(Source: Department of Transport and Main Roads (DTMR))

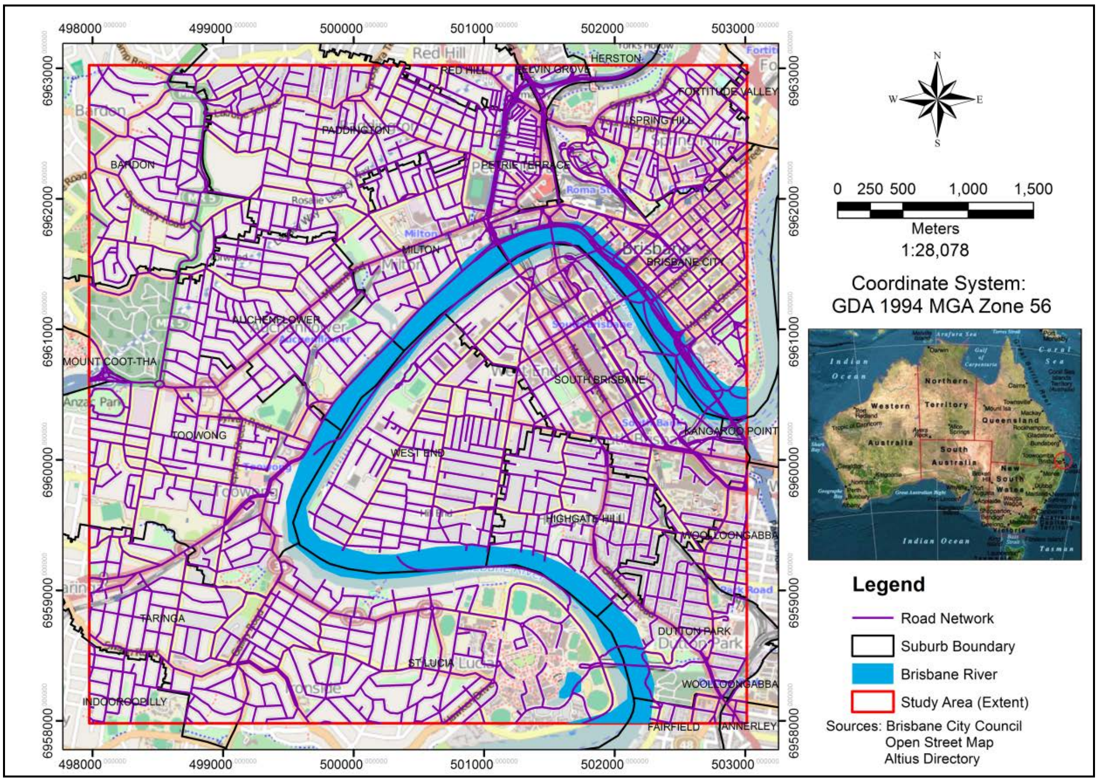


Figure 5.9 The road network map of the study area

On the other hand, the rail infrastructure in Queensland is owned by the state government through the Queensland Rail (QFCI 2012). The company operates the rail network that connects people around Queensland and Brisbane City for transportation and travel as shown in Figures 5.10 and 5.11 (Queensland Rail 2014). However, the 2010/2011 floods affected more than 3,000 km of the rail network across the state (QFCI 2012). In Brisbane, the passenger network was almost operational within six hours of flood (QFCI 2012).

Figure 5.10 The Queensland rail network
(Source: Queensland Rail and Translink)

Figure 5.11 The train network map of Brisbane City
(Source: Queensland Rail and Translink)

To assess the vulnerability of road and rail networks within the study area, the road and rail networks were overlaid with the flood risk and climate adaptation capacity maps. The simple overlay analysis of ArcGIS 10 was instrumental in analysing the vulnerability of the road and network system. The analysis showed that

approximately170km (47%) of road and 2.5km (38%) of rail networks were identified within very highly risk and low adaptation capacity (see Figure 5.12).
One of the significant issues during the January 2011 flood was the isolation of some residential areas, hospitals and aged care facilities in Brisbane City. To help minimise the impacts of isolation, the functional model of the road network system was implemented for emergency evacuation management with the algorithms presented in the following subsection.

Road Network Model for Evacuation Routing

The road and rail network vulnerability map presented in Figure 5.12 was applied in this study to find the best evacuation route. The network components defined in the analysis were the road networks, locations of bus stops and the January 2011 flood evacuation centres.
In establishing the network connectivity rules of the road, the evacuation route analysis layer was created in ArcGIS 10 using the network analysis tool with three categories – the bus stops, areas of very high flood risk or low adaptation capacity as the barriers, and the evacuation routes. The identification of bus stops was based on near distance analysis selecting ≤ 100-meter distance between the bus stops and centroid locations of buildings within areas occupied by very high flood risk and low adaptation capacity. From existing literatures and news reports, two evacuation centres were set up as temporary shelters for the affected families by the city government of Brisbane.

The evacuation route analysis revealed two possible routes leading to evacuation centres: one going to the first evacuation centre (i.e. RNA Show Grounds) and the other one going to the second evacuation centre (i.e. QEII Stadium). The first evacuation route was identified to have 71 bus stops and second evacuation route has 31 bus stops 21 km and 20.7 km travel distances, respectively. On the average, the time to travel between bus stops is 0.60 minutes and 1.38 minutes within the study area leading to evacuation route 1 and evacuation route 2, respectively.

Tables 5.5 and 5.6 summarise the bus stops, distance between previous and succeeding bus stops, and travel times to be spent during evacuation. The calculated travel times indicated in the Tables assumed the 30 km/h driving speed limit and excluded the time spent for passenger's boarding and embarking. Also significant to consider in the analysis was the selection of bus stops because its number and location significantly affect the evacuation routing system. In this study, all possible bus stops were included in the analysis within 100-meter distance except for those that were flagged of having no road network connections. Certainly, the option and flexibility of choosing bus stops can be made available to emergency managers.

The information provided in Tables 5.5 and 5.6 will help affected people on areas of very high flood risk and low adaptation capacity to identify accessible bus stops and closest flood evacuation centre. These will also give them the idea of travel time required between bus stops and expected time of arrival to their chosen evacuation centre.

Table 5.5 The study area's potential road route to evacuation centre 1 (RNA Show Grounds)

Bus Stop (No.)	Distance between bus stops (m)	Travel time (min)	Bus Stop (No.)	Distance between bus stops (m)	Travel time (min)
1	0.00	0.00	39	8.57	0.02
2	10.86	0.02	40	332.46	0.66
3	1229.38	2.46	41	421.52	0.84
4	571.79	1.14	42	0.41	0.00
5	94.57	0.19	43	1230.07	2.46
6	627.20	1.25	44	26.10	0.05
7	35.90	0.07	45	48.21	0.10
8	1069.29	2.14	46	405.49	0.81
9	154.02	0.31	47	21.12	0.04
10	177.64	0.36	48	203.06	0.41
11	72.55	0.15	49	17.23	0.03
12	55.70	0.11	50	18.98	0.04
13	145.16	0.29	51	223.23	0.45
14	30.00	0.06	52	122.30	0.24
15	708.45	1.42	53	232.42	0.46
16	173.05	0.35	54	91.77	0.18
17	542.30	1.08	55	132.04	0.26
18	437.95	0.88	56	28.37	0.06
19	10.85	0.02	57	1167.99	2.34
20	133.59	0.27	58	35.57	0.07
21	227.68	0.46	59	318.38	0.64
22	90.91	0.18	60	42.91	0.09
23	884.62	1.77	61	125.17	0.25
24	12.23	0.02	62	116.63	0.23
25	466.72	0.93	63	64.99	0.13
26	1296.84	2.59	64	123.46	0.25
27	26.09	0.05	65	245.52	0.49
28	616.14	1.23	66	17.67	0.04
29	1331.00	2.66	67	2.09	0.00
30	47.27	0.09	68	214.76	0.43
31	674.16	1.35	69	41.06	0.08
32	92.82	0.19	70	18.58	0.04
33	118.28	0.24	71	941.28	1.88
34	42.80	0.09	Total	21,088.25	42.18
35	773.88	1.55	**Average**	**301.26**	**0.60**
36	31.39	0.06			
37	253.13	0.51			
38	782.64	1.57			

Table 5.6 The study area's potential road route to evacuation centre 2 (QEII Stadium)

Bus Stop (No.)	Distance between bus stops (m)	Travel time (min)	Bus Stop (No.)	Distance between bus stops (m)	Travel time (min)
1	0.00	0.00	18	190.11	0.38
2	3537.95	7.08	19	471.33	0.94
3	71.38	0.14	20	16.55	0.03
4	3042.91	6.09	21	381.18	0.76
5	2687.26	5.37	22	142.42	0.28
6	2360.51	4.72	23	296.60	0.59
7	120.86	0.24	24	345.55	0.69
8	255.55	0.51	25	21.10	0.04
9	102.99	0.21	26	501.58	1.00
10	224.15	0.45	27	232.78	0.47
11	264.23	0.53	28	44.75	0.09
12	56.33	0.11	29	410.97	0.82

Bus Stop (No.)	Distance between bus stops (m)	Travel time (min)	Bus Stop (No.)	Distance between bus stops (m)	Travel time (min)
13	173.05	0.35	30	322.29	0.64
14	52.73	0.11	31	3784.59	7.57
15	356.72	0.71	Total	20,733.04	41.47
16	100.38	0.20	**Average**	**691.10**	**1.38**
17	164.24	0.33			

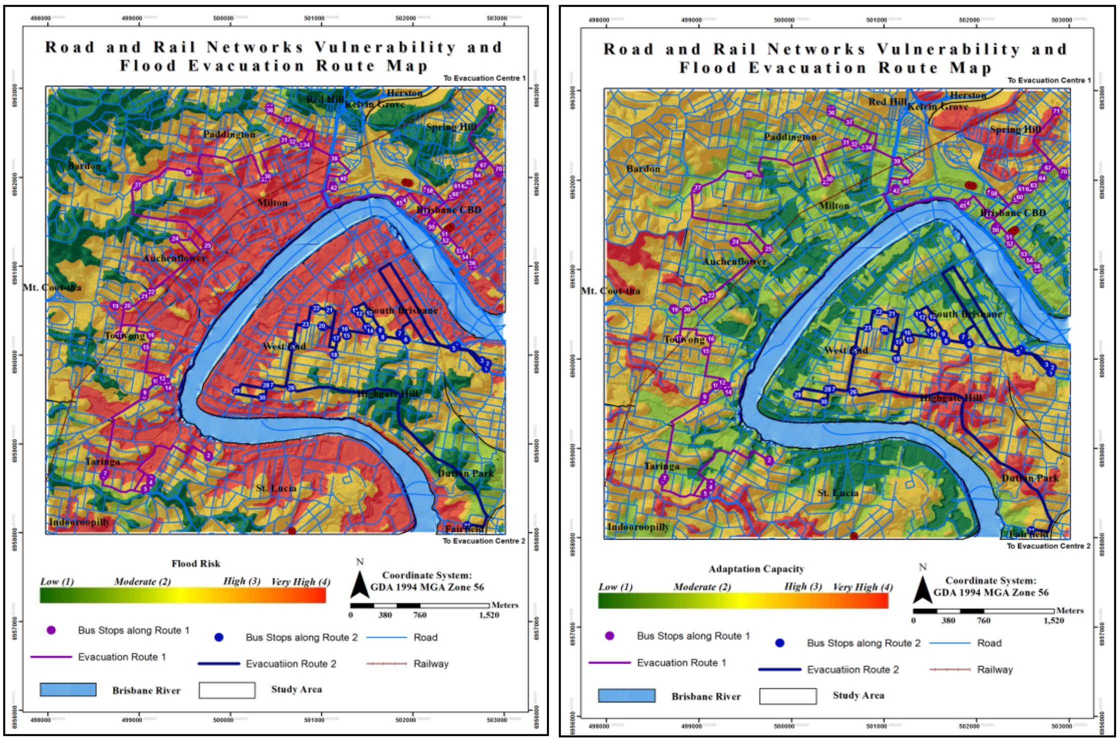


Figure 5.12 The road and rail networks vulnerability and flood evacuation route maps using flood risk (left) and climate adaptation capacity (right) models

5.3.1.3 Water Supply Network Model

The Queensland's water supplies and related infrastructures are owned and managed by 170 registered service providers (QCA 2013). For the South East Queensland region in Australia, the water infrastructure network is being provided by the SEQ Water Grid. The SEQ Water, a merger of three state-owned businesses on 01 January 2013 – the SEQ Water Grid Manager, LinkWater and former SEQ Water, is responsible for the long-term planning of the region's water supply and the management of more than $10 billion of assets and natural catchments (SEQ Water 2013b) as shown in Figure 5.13. To achieve the long-term security of the region, the South East Queensland Water Strategy was developed using a water balance model that considers climate variability, population growth and other regional factors affecting supply and demand (SEQ Water 2013 b).

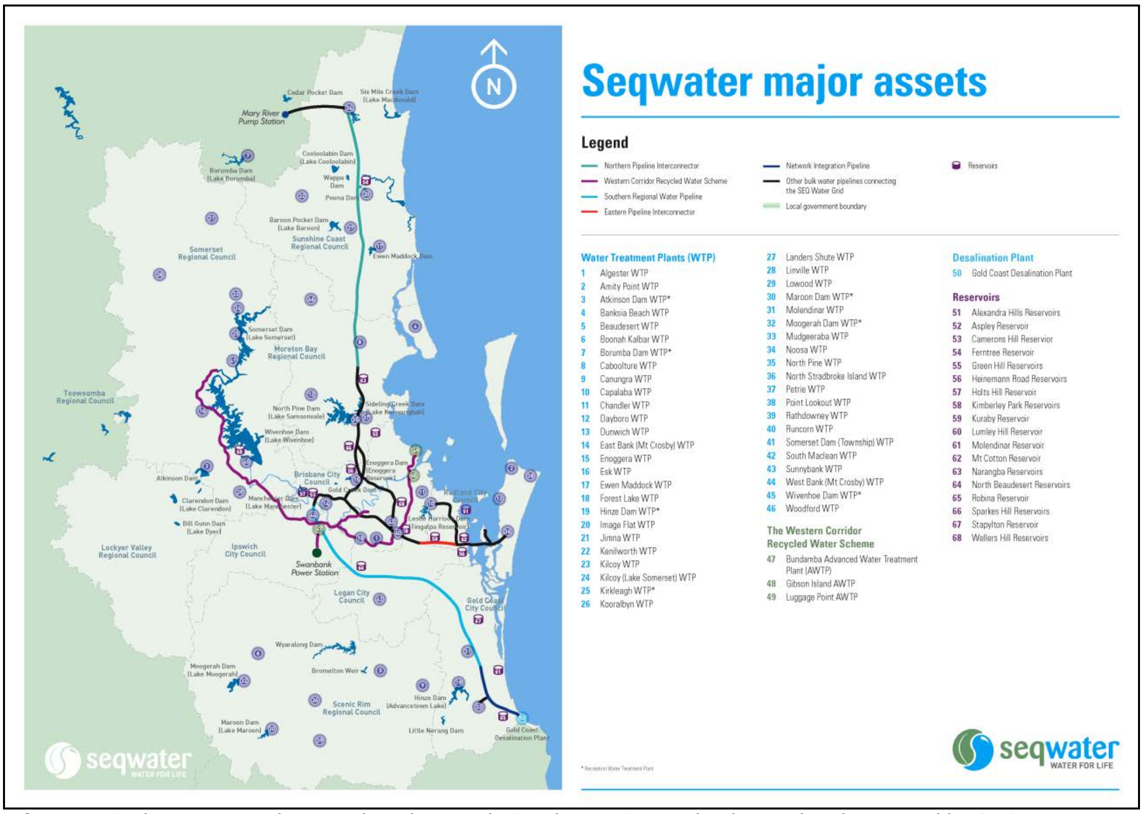


Figure 5.13 The water supply network and assets in South East Queensland owned and managed by SEQ Water (Source: SEQ Water 2013)

In order to provide a consistent framework and benchmarks for the planning and design of urban water supply and sewerage infrastructure, the Queensland Government developed the guidelines for water supply and sewerage in 2010 (DEWS 2013). However, the report was released a few months before the 2010/2011 flood events.

In Brisbane City, the city council developed the Water Supply Infrastructure Contributions Planning Scheme Policy (PSP) to provide background and contributions information on infrastructure for its water supply network (BCC 2009c). Furthermore, the policy was also developed to comply with the Integrated Planning Act 1997 which requires integration of land use and infrastructure planning to allow infrastructure to be supplied in a coordinated, efficient and orderly manner (BCC 2009c).

As shown in Figure 5.14, the water supply PSP of the city sets contributions for the trunk water supply network that services the future population including bulk supply and treatment, reservoirs, pump stations, booster stations and pipes (BCC 2009c).

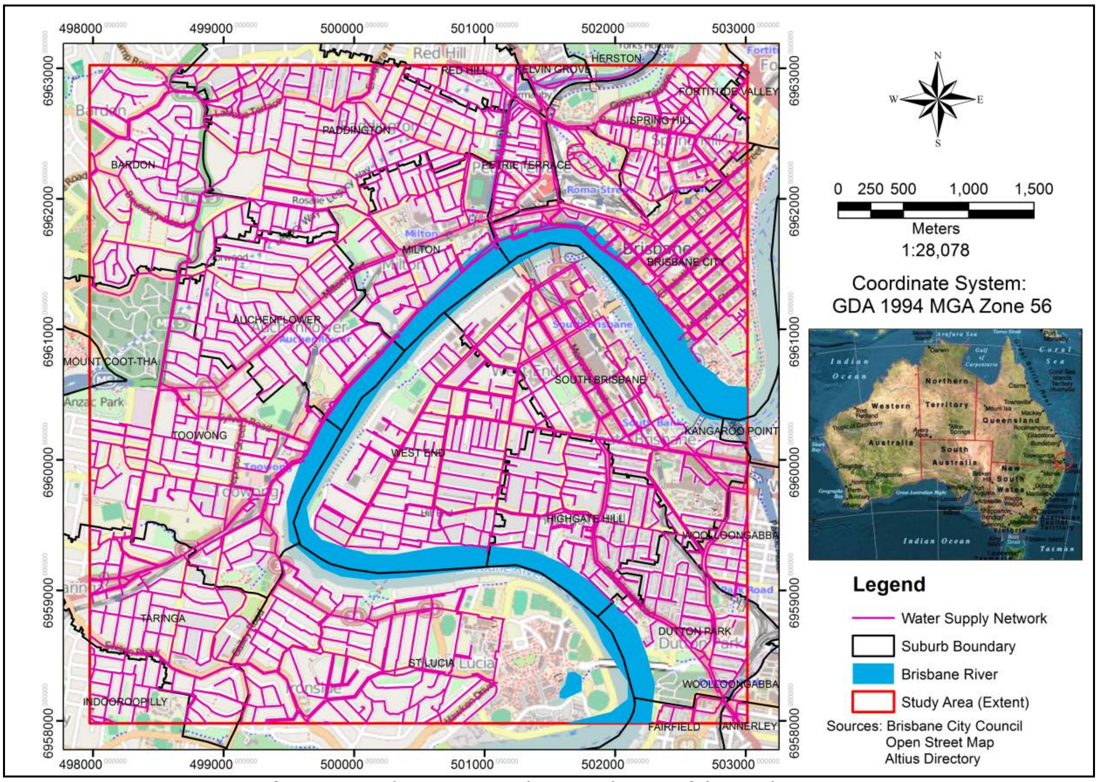


Figure 5.14 The water supply network map of the study area

Considering that the water supply problem during the January 2011 flood, which had been also experienced during the January 2013 flood, was more on water turbidity (Keller 2013 and News Limited 2013), this study examined the vulnerability of water supply by identifying the potential flow of turbid water along the trunk-reticulation mains. Using the network analysis tool of ArcGIS 10, water supply network components were defined as nodes and edge in the network model as presented in Table 5.7.

Using the results from the flood risk and adaptation capacity assessments in the water supply network vulnerability assessment, eight (8) out of 107 trunk-reticulation main connection points (as potential entry points of turbid water or source component of the network) were assessed as highly vulnerable critical water supply assets being found within areas of very high flood risk and very low adaptation capacity (see Table 5.7). Flagging them as critical junctions (see blue square dots in Figure 5.15) in the Utility Network Analysis of ArcGIS 10, the potential path of turbid water through the trunk-reticulation mains was traced and the total linear kilometre was then calculated. Results of the analysis revealed that turbid water may flow along 246 km water distribution lines in the North East and North West based on the January 2011 flood event. This comprises 56% of the water pressure mains within the study area which may potentially affected by supply of turbid water.

Table 5.7 Counts of highly to very highly vulnerable critical water supply network assets

Water Supply Network Asset	Role	Total	Highly to Very Highly Vulnerable	Percent of Total
Pressure Gauge (No.)	Intermediate Node	13	0	0
Flow Meter (No.)	Intermediate Node	61	11	18
Booster Pump (No.)	Intermediate Node	1	0	0
Control Valve (No.)	Intermediate Node	1990	268	13
Fitting (No.)	Intermediate Node	2011	205	10
System Valve (No.)	Intermediate Node	5010	636	13
Trunk-Reticulation Main Connections (No.)	Source	107	8	7
Pressure Main (Length in Km.)	Edge	435	246	56
Endpoint of Trunk-Reticulation Connections	Sink	2205	_	_

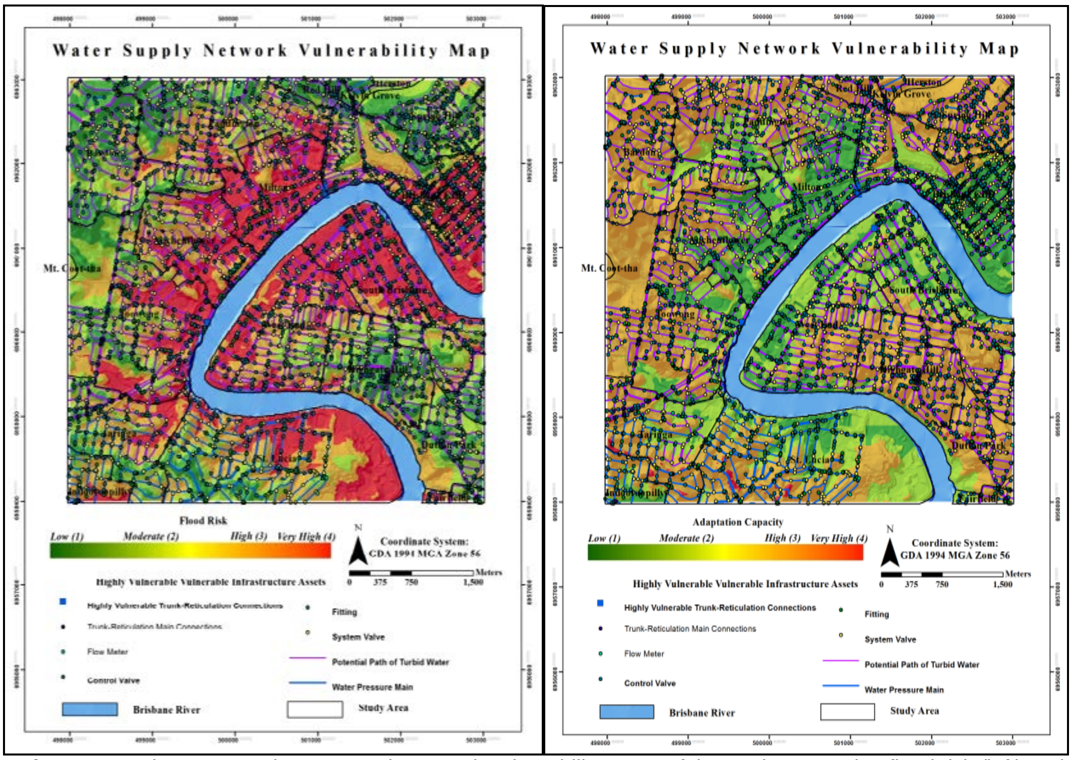


Figure 5.15 The generated water supply network vulnerability maps of the study area using flood risk (left) and climate adaptation capacity (right) models

The results from this analysis can assist the water supply industry to evaluate the susceptibility of water system to “dirty water” event. The analytical tool and the information generated from this study can help alleviate a range of consequences or impacts such as water-borne diseases from any flood event. During the January 2011 flood, no report was made regarding any breakdown of water supply infrastructure and water shortage except for the quality of drinking water in some areas. Nonetheless, it is noteworthy to take into account the potential flood impacts that may disrupt the entire water supply system.

5.3.1.4 Sewerage Network Model

In most parts of Queensland, the public sewerage systems are managed by public authorities (i.e. councils) except in the south-east where sewerage systems are managed by specialised service providers known as "distributor-retailers" (QFCI 2012). Governed by an independent board, Brisbane and Ipswich City Councils, and the Lockyer Valley, Scenic Rim and Somerset Regional Councils owned a distributor-retailer Queensland Urban Utilities which has the primary role of delivering drinking water, recycled water, and wastewater services to the cities and townships within the boundaries of those five council areas (QUU 2011b). This system of the administration of water and sewerage networks was directed through the South East Queensland Water (Distribution and Retail Restructuring) Act 2009 (QFCI 2012).

Pursuant to the Act, the Queensland Urban Utilities are required to prepare the Water Netserv Plan which was provided in two parts: Part A provides an overview of the water and wastewater networks and services, and broad description of the system. Part B, on the other hand, provides an overview of our operating framework, processes, performance and management functions (QUU 2011b). As the key strategic documents, the Plan highlights the importance of responding to emergencies such as the 2010/2011 SEQ floods.
In Brisbane, the sewerage network is designed in accordance with the City's Sewerage Infrastructure Contributions Planning Scheme Policy (PSP) as shown in Figure 5.16. Pursuant to the Integrated Planning Act 1997, the Policy outlines the general approach to infrastructure planning and contributions for the sewerage network for Brisbane (BCC 2009d).

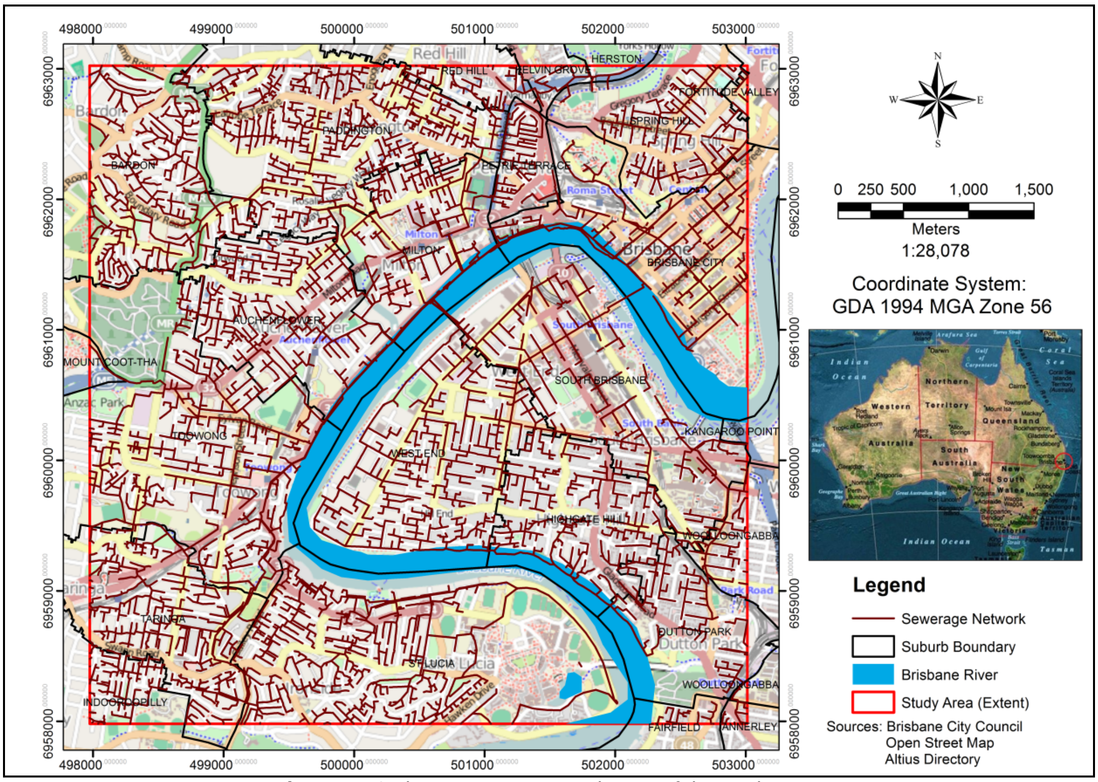


Figure 5.16 The sewerage network map of the study area

The impacts of the 2010/2011 floods on sewerage infrastructure include the damage and inundation of the system which resulted in the discharge of untreated sewage through overflow relief structures and backflow of sewage into private properties in the Brisbane area (QFCI 2012). The overflow of untreated or contaminated sewage with floodwaters entering waterways near residential areas and public parks posed risk to human health (Jensen 2009 and QFCI 2012). In one of the recommendations made by QFCI (2012), the Queensland Government should consider including in the criteria in the Queensland Plumbing and Wastewater Code a requirement that the risk of leakage from private on-site sewerage systems during floods be minimised. As initial response to this recommendation, this study was conducted to assess the vulnerability of sewerage network in Brisbane City.

In creating the network connectivity rules, the functional roles of the components of the sewerage infrastructure network were defined according to its operational characteristics as summarised in Table 5.8. From the table, the topological sewage source and sewerage endpoint were derived by extracting the beginning points and ending points of the sewerage main/reticulation networks, respectively.

Using the results from the flood risk and adaptation capacity assessments in the sewerage network vulnerability assessment, 455 out of 2525 sewage sources (as assumed points of sewerage blockage) were assessed as highly vulnerable sewerage network assets being found within areas of very high flood risk and very low adaptation capacity (see Table 5.8). Flagging them as critical junctions in the Utility Network Analysis of ArcGIS 10, results of the analysis revealed that 33 km (91%), 32 km (78%), and 16 km (81%) of the sewerage main trunk, reticulation, and pressure rising networks were potentially affected by the January 2011 flood. The information provided in Table 5.8 and Figure 5.17 will assist sewerage infrastructure management to comply with the maintenance requirements of the sewerage system set forth in the Queensland Plumbing and Wastewater Code Guidelines. Furthermore, these results will aid in addressing the issue raised by QFCI (2012) that the aspect of flood resilience in sewerage infrastructure was not a specific performance criterion in the Code.

Table 5.8 Counts and lengths of highly vulnerable critical sewerage network assets

Sewerage Network Asset	Role	Total	Highly Vulnerable	Percent of Total
Sewage Source (No.)	Source	2525	455	16
Sewerage Endpoint	Sink	2932	-	-
Main Intersection (No.)	Intermediate Node	313	185	59
Pump Station (No.)	Intermediate Node	10	5	50
Wet Well (No.)	Intermediate Node	1	1	100
Storage Facility (No.)	-	2	1	50
Main Trunk (km)	Edge	33	30	91
Main Reticulation (km)	Edge	32	25	78
Reclaimed Water (km)	Edge	1.5	0	0
Main Pressure Rising (km)	Edge	16	13	81

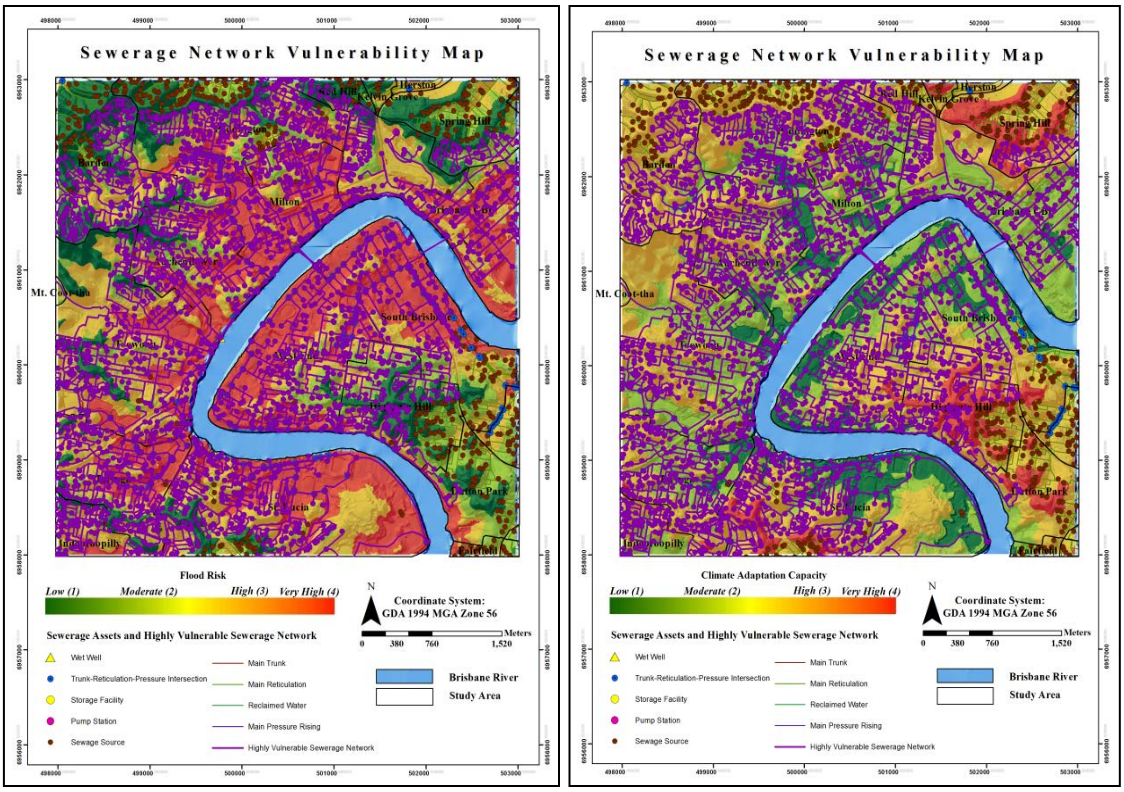


Figure 5.17 The sewerage network vulnerability maps of the study area using flood risk (left) and climate adaptation capacity (right) models

5.3.1.5 Stormwater Network Model

The Queensland system for urban stormwater management is governed by a variety of state, regional and local policies. The planning of urban stormwater management in the State was strengthened by the amendment of the Environmental Protection (Water) Policy 2009 (EPP Water) placing urban stormwater in a total water cycle management context and the approval of the State Planning Policy 4/10 Healthy Waters (SPP Healthy Waters) 2010 (EHP 2010). As the primary water quality management legislation in Queensland, the Environmental Protection Act 1994 (EP Act) provides the statutory framework for setting and achieving environmental values (EVs) and water quality objectives (WQOs) in the State (EHP 2010). Shown in Figure 5.18 is the map of the EPP Water Schedule 1 with catchment-specific EVs and WQOs within Moreton Bay/South East Queensland waters wherein the study area is a part of.

During the 2010/2011 floods in the South East Queensland, stormwater contributed to flooding in various areas which were characterised in two types: (1) basement flooding; and (2) backflow flooding (QFCI 2012). In response to the Queensland Floods Commission of Inquiry recommendations, the Department of Energy and Water Supply (DEWS) conducted a review of the Queensland Urban Drainage Manual (QUDM). Through this manual, the government aimed to provide details of technical and regulatory aspects to consider during the planning, design and management of urban stormwater drainage systems, and to provide details of appropriate design methods and computational procedures including the hydrologic and hydraulic procedures and environmental and legal aspects (DEWS 2013c).

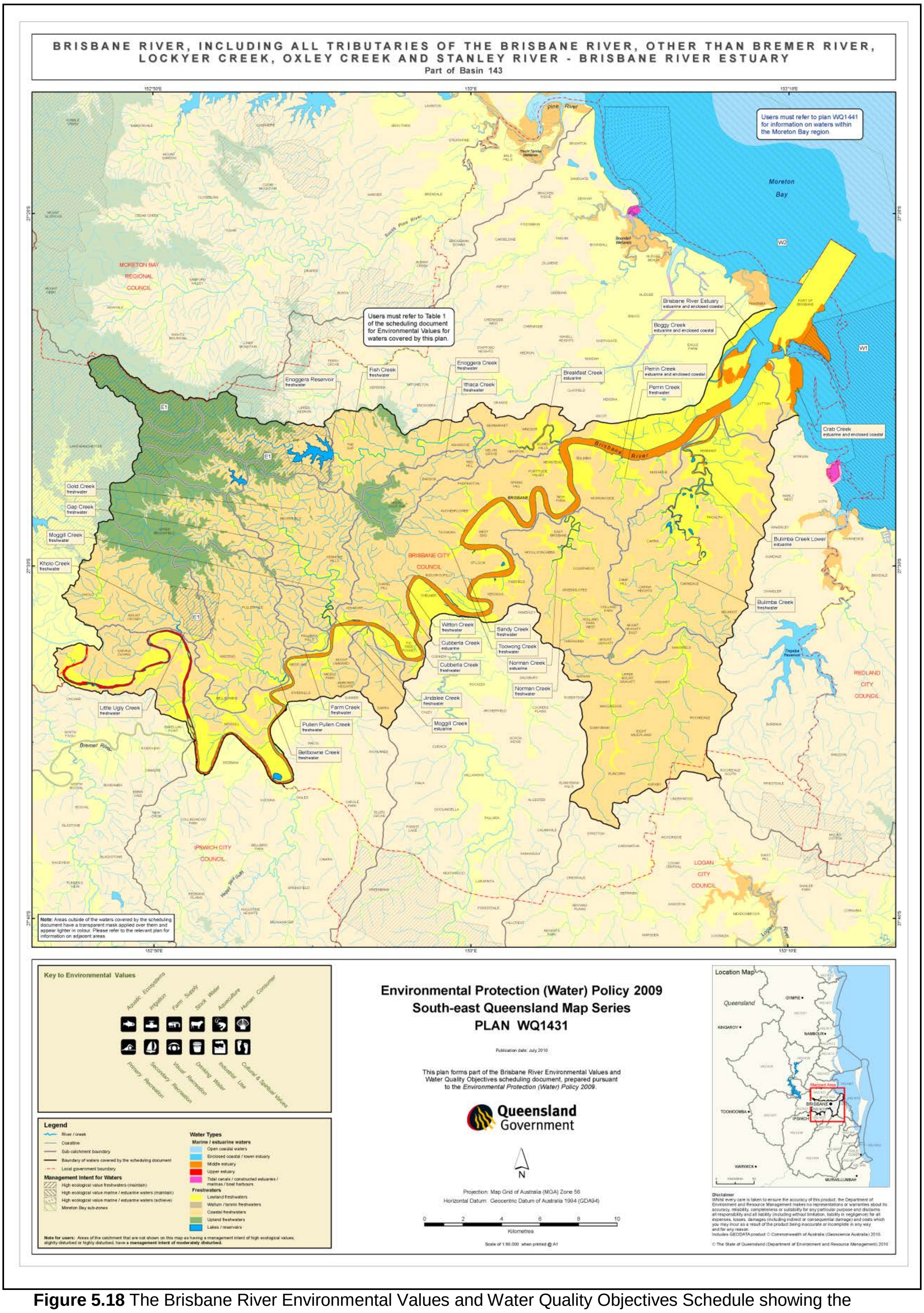


Figure 5.18 The Brisbane River Environmental Values and Water Quality Objectives Schedule showing the coverage of urban stormwater infrastructure (Source: DERM 2010 and EHP 2010)

In the draft new City Plan prepared by Brisbane City Council, stormwater is one of the five trunk infrastructure networks intended for drains, water quality treatment, and flood mitigation (BCC 2013b). The City Council has 2640 km of enclosed stormwater pipes as shown in Figure 5.19 (Arnison *et al.* 2011). One of the desired standards of service for the stormwater network is to collect and convey stormwater flows during flood events with minimal effects to communities and damage to properties (BCC 2012c). Also embodied in the City's Waterways Planning Scheme Policy (PSP), stormwater infrastructure was analysed to address contributions and requirements for waterways infrastructures at the catchment level (BCC 2009e).

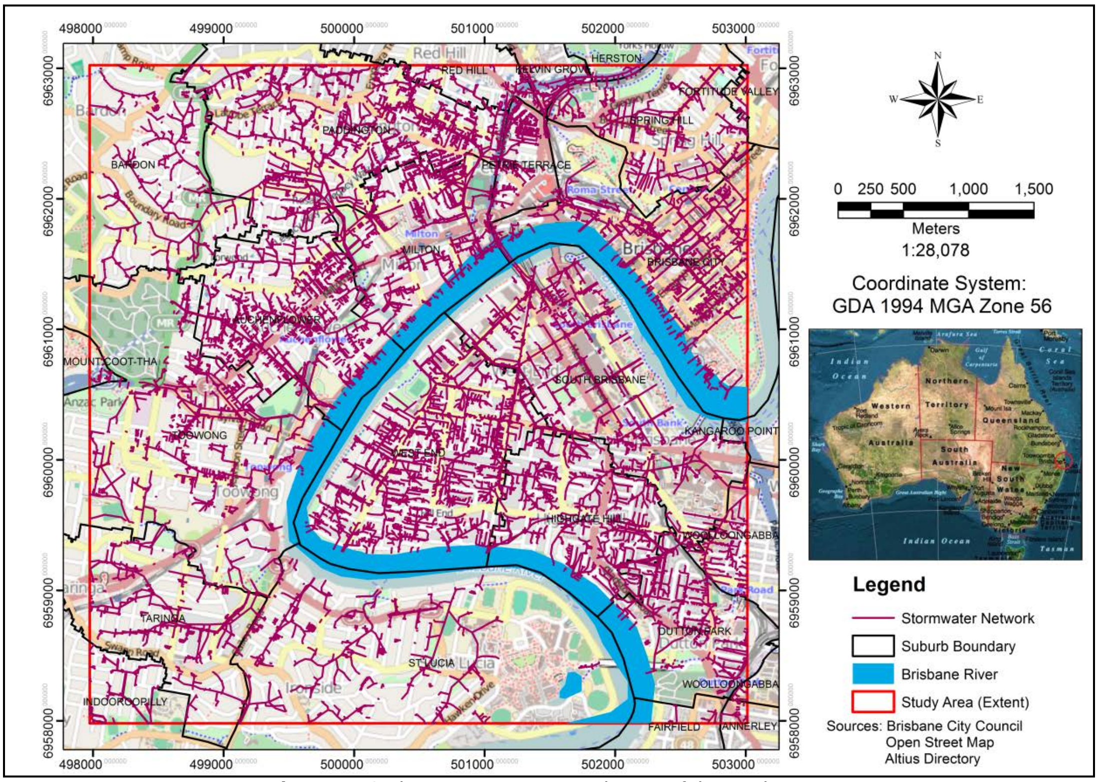


Figure 5.19 The stormwater network map of the study area

In a report prepared by Bannan (2011a) and QFCI (2012), all parts of the stormwater network require inspection for maintenance and system's upgrade. Apart from being an aged infrastructure, which was constructed in 1860 to serve a population of approximately 5000, the pipes in flood-affected areas are likely to have been silted (Bannan 2011a and QFCI 2012). To help improve the performance of the stormwater infrastructure, QFCI (2012) recommended that councils should periodically conduct risk assessments to identify areas at risk of backflow flooding and consideration of the installation of backflow prevention devices.

With the purpose of providing aid in the management of stormwater drainage system in Brisbane City and in support to QFCI recommendations, the vulnerability of the network was assessed using geographic information system. However, this study focused mainly on the available components of stormwater networks disregarding the issues of illegal connections of stormwater to sewerage infrastructure. In doing the analysis, the utility network analysis tool of ArcGIS was utilised once again to establish the connectivity rules among stormwater pipes, gullies and inlets to the stormwater drains. In the analysis, stormwater pipe outlets, end caps, and flood gates were assumed to have been accumulated with silt that may potentially cause damage to stormwater pipes.

Utilising the results from the flood risk and adaptation capacity assessments of the stormwater network, the overlay analysis revealed that 83, 13, and 4 pipe end outlets, end caps, and flood gates, respectively, were highly vulnerable to flooding. Using them as flag junctions in the utility network analysis, the result revealed that approximately 87 km of stormwater pipes were potentially affected by flooding due to siltation within the study area. This comprises 19% of the 450 km of the flood-affected pipes as reported by Bannan (2011) and QFCI (2012). Figure 5.20 shows the highly vulnerable stormwater network within areas of very high flood risk and low climate adaptation capacity. The maps shown below will provide locational information to focus on those parts of the stormwater drainage network with pollutants and silts that would tend to accumulate and consequently affect the effective performance of stormwater pipes.

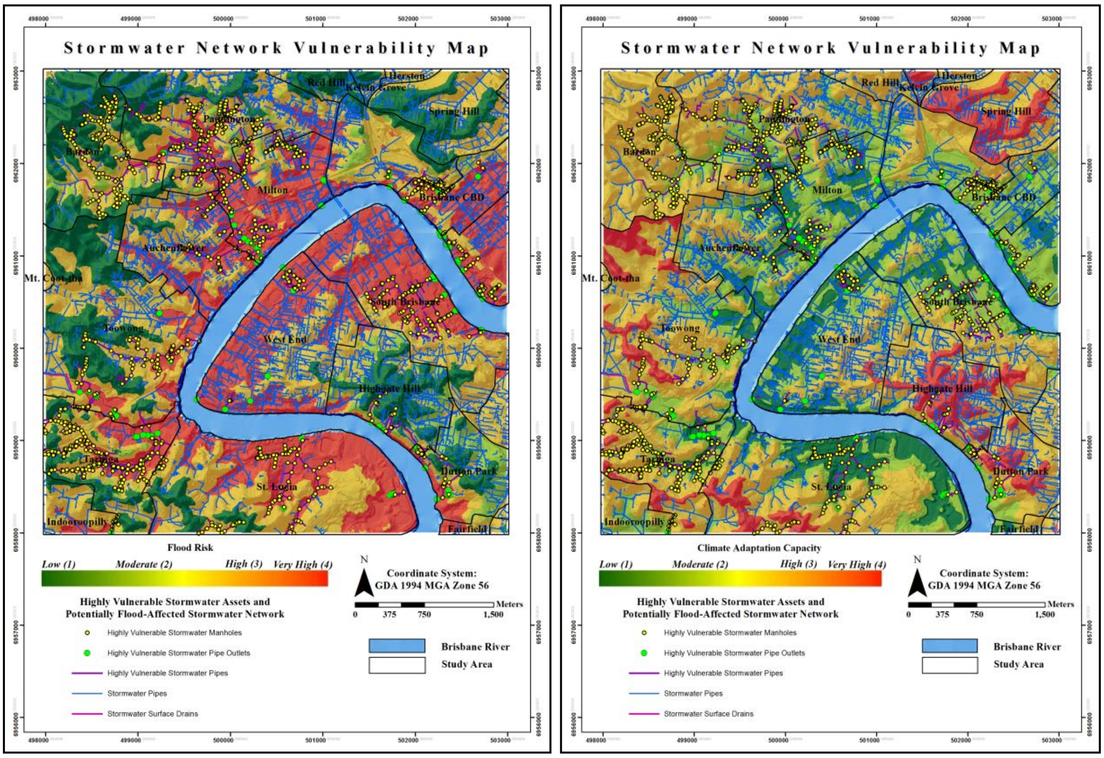


Figure 5.20 The stormwater network vulnerability maps of the study area using flood risk (left) and climate adaptation capacity (right) models

5.3.2 Critical Infrastructure Interdependencies

Using the results from the vulnerability assessments of individual networks, the highly vulnerable infrastructures assets were joined in Figure 5.21 to initially set its geographical interdependency. The figure depicts the overall interdependency of critical infrastructures (electricity, transportation, sewerage, stormwater, health care infrastructure, and building properties). The background map in Figure 5.21 was derived from the flood risk and climate adaptation capacity assessments presented in Chapter 4. On the other hand, the vulnerable infrastructures shown in the foreground were taken from the utility network modelling specified in Section 5.2.3.1 of this Chapter.

Either the interdependency of these infrastructures is bidirectional (Rinaldi *et al.* 2001) or unidirectional (Johansson and Hassel 2010), the failure state of one infrastructure or several infrastructures due to January 2011 flooding had significant effects on the state of other infrastructures on which the latter depends upon. From this view, the specific critical infrastructure interdependencies are discussed in the subsequent sections.

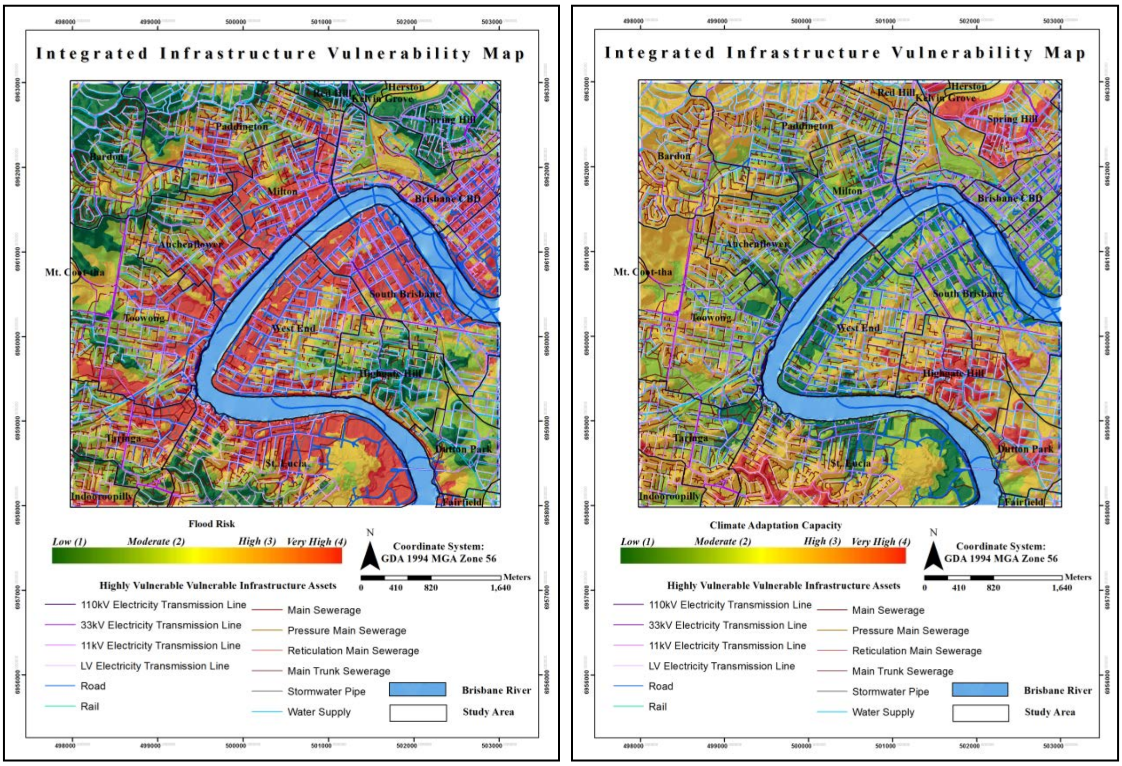


Figure 5.21 The integrated infrastructure vulnerability maps of the study area using flood risk (left) and climate adaptation capacity (right) models

This section starts the discussion with the operational strategies of an "external" infrastructure - the Wivenhoe Dam. It was built in 1984 as a dual-purpose storage both for water supply and flood mitigation (SEQ Water 2012). The dam was designed to hold back 1.45 million megalitres during floods and 1.15 million megalitres for normal storage capacity (SEQ Water 2013). Along with heavily soil-saturated catchment due to torrential rains, the releases of water from the Wivenhoe Dam raised the water levels in the Brisbane River by up to 10 metres during the January 2011 flood (Calligeros 2011). Faulted of aggravating the damage downstream, the dam operators made sub-optimal decisions by neglecting the forecasts of further rainfall and assuming a "no rainfall scenario" (van den Honert and McAneney 2011).

The January 2011 flood event cascaded failures of the critical infrastructures in Brisbane City such as power outages, road cuts, isolation of residential premises, down of communication lines, among others. The failures that spread across the Brisbane City in relation to the extreme climatic event were described in this study as functional, geographical, direct or indirect interdependency (Rinaldi *et al.* 2001 and Johansson and Hassel 2010). However, the limitations of clearly delineating these types of interdependencies are acknowledged in this Chapter.

The functional failure of the ENERGEX to supply electricity to other critical infrastructures, either caused by direct flood damage or pre-emptive measures, can be explicitly distinguished in Figure 5.22. A good example was the inability of the electricity infrastructure to supply the demanded service to other critical infrastructures such as built-up premises, railway system, sewerage system, and health care facilities. The effect of removing the dependency edge from the functional model rendered the electricity unavailable both to flooded and non-flooded premises. The devastation caused 300,000 customers in Ipswich and Brisbane to lose power. Furthermore, 35% of Ergon Energy's distribution area was disrupted primarily due to the pre-emptive measures taken during the 2010/2011 floods (QFCI 2012).

The co-location and close proximity of electricity infrastructure, residential premises, railway, sewerage, and health care facilities on areas characterised by very high flood risk or low adaptation capacity (see Figure 5.23 for example) rendered these critical infrastructures to become highly vulnerable. Hence, the consequences due to the severe weather conditions affecting the operation of electricity-dependent infrastructures were influenced by geographically-confined strain, a term that describes a removal of network component/s (Johansson and Hassel 2010). The removal of geographically-located electrical points from rail yards, for example, to reduce the flood impacts to the railway's electrical system (Ford and Timmins 2011, QFCI 2012) caused the railway network non-functional.

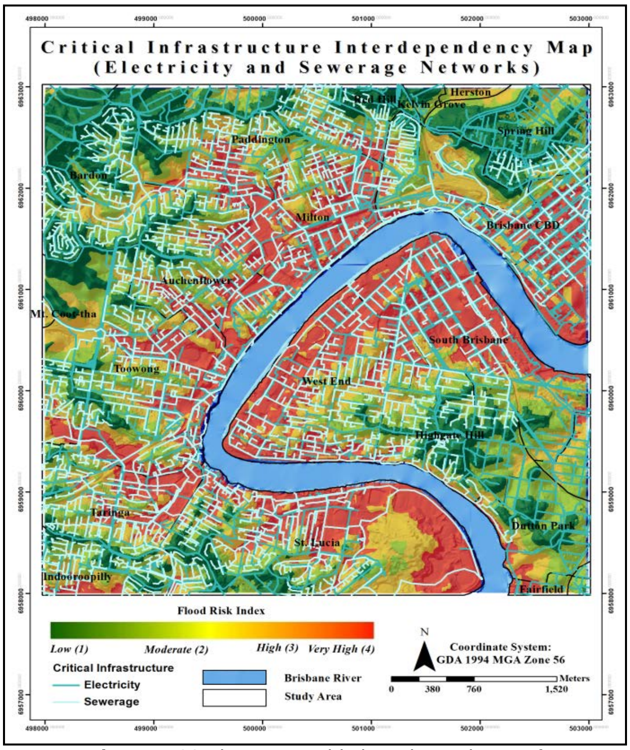


Figure 5.22 The geographic interdependency of electricity and sewerage networks

As an example of direct or first order interdependency (Johansson and Hassel 2010), the failure of electricity infrastructure (i.e. non-operational generators and switchboards) directly affected the sewerage system and positioned its treatment systems into critical failure (Lewis 2011 and QFCI 2012). Furthermore, the health care facilities were also at risk of being cut of electricity supply due to flooding, which would have necessitated the evacuation of all patients (Prado 2011, QFCI 2012).

On the other hand, the indirect or higher order interdependency (Johansson and Hassel 2010) was explicitly characterised by the exposure of public to health issues such as when contaminated sewage potentially leaked from private on-site sewerage systems. Then, services of health care facilities were inaccessible due to flood isolation and unavailability of electricity supply. Due to risk of power outage, the evacuation of patients from the health care facilities was likewise infeasible due to access of evacuation routes was completely lost from inundation (QRA 2011, QFCI 2012). In some cases, vehicle access, including ambulance access, to and from the hospital was cut (Prado 2011a, 2011b, QFCI 2012). In the higher order interdependency, the ripple effects of electricity failure were realised from electricity failure down to inaccessibility of roads for emergency evacuation (see Figure 5.23).

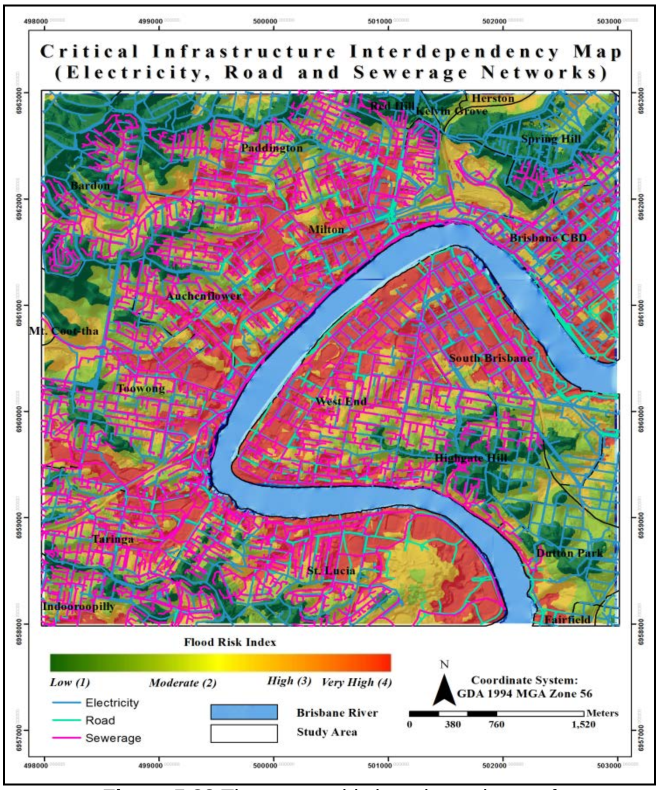


Figure 5.23 The geographic interdependency of electricity, road, and sewerage networks

In this study, however, it can be postulated that indirect interdependency may not be characterised solely on the basis of higher order interdependency. The January 2011 flood demonstrated that indirect interdependency may be described by a partial disruption of the critical infrastructure services despite the failure of other dependent infrastructure. An example was that the effects of failure of the communication infrastructure to deliver the desired services to a healthcare facility of manageable size may not be as enormous to that of the failure of electricity infrastructure to supply power to health care facilities across the flooded areas. The thesis behind this argument is that direct or indirect interdependency would depend on the types of critical infrastructures, the amount of services they provide, and the amount demanded by other infrastructures. However, this theory agrees with Johansson and Hassel's (2010) argument that interdependent relationship of infrastructure systems can be characterised either on macro- or micro-perspective.

Additionally, the poorly designed or maintained stormwater networks, in combination with riverine flooding, provided limited flood mitigation benefits (QFCI 2012). Stormwater flooding and backflow flooding of the stormwater network caused basement damage to a number of high rise buildings and residential properties particularly in the low lying areas of Brisbane and the central business district (QFCI 2012). The functional failure of the stormwater network was further exacerbated when the network was "illegally" connected to the sewerage network (Lewis 2011, QFCI 2012). Thus, the undesirable effects to the sewerage system were amplified once again to significantly bring on board the interconnected and ripple effect issues on health, power outages, and problems on evacuation management. Hence, this study can provide an analytical tool for monitoring the connectivity, if any, between sewerage and stormwater infrastructures for regulatory purposes (see Figure 5.24).

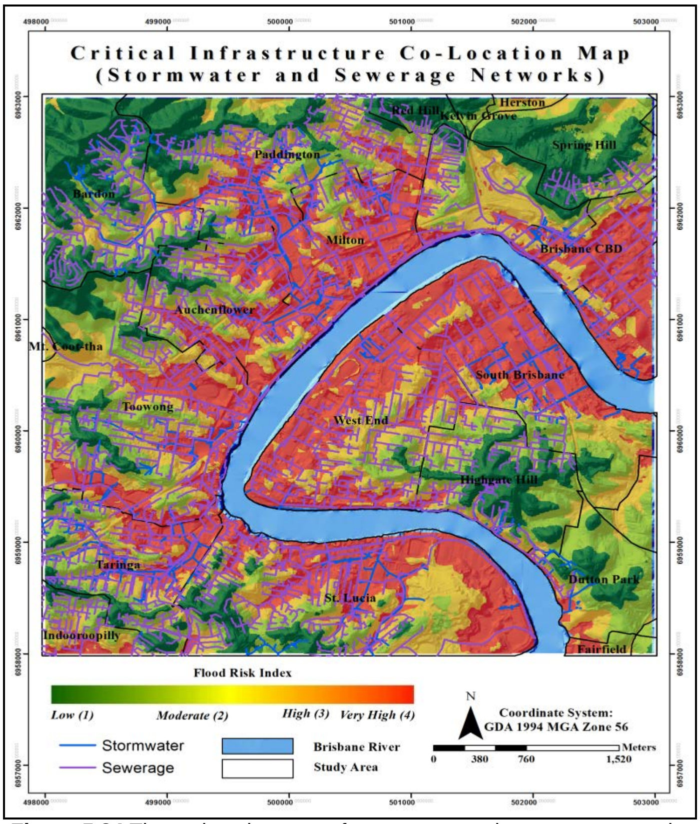


Figure 5.24 The co-location map of stormwater and sewerage networks

Finally, most researchers neglected the concept of nil interdependency of critical infrastructures and that it can occur despite they share geographical locations. Taking the example of stormwater during the January 2011 flood, the operation of the infrastructure did not depend mainly on electricity infrastructure. A word of caution, however, unless the stormwater network was designed with electric pumps then the interdependency could have been existed. During the January 2011 flood, no such case was reported with the Queensland Floods Commission of Inquiry (QFCI). Hence, this observation was assumed to be factual.

In a nutshell, this study exemplified the interdependencies of urban community's critical infrastructures in relation to extreme weather event. Characterised of having functional, geographical, direct, indirect, or even nil interdependencies, these bilateral or unilateral relationships that aroused in the critical infrastructures due to the January flood event in Brisbane are graphically summarised in Figure 5.25.

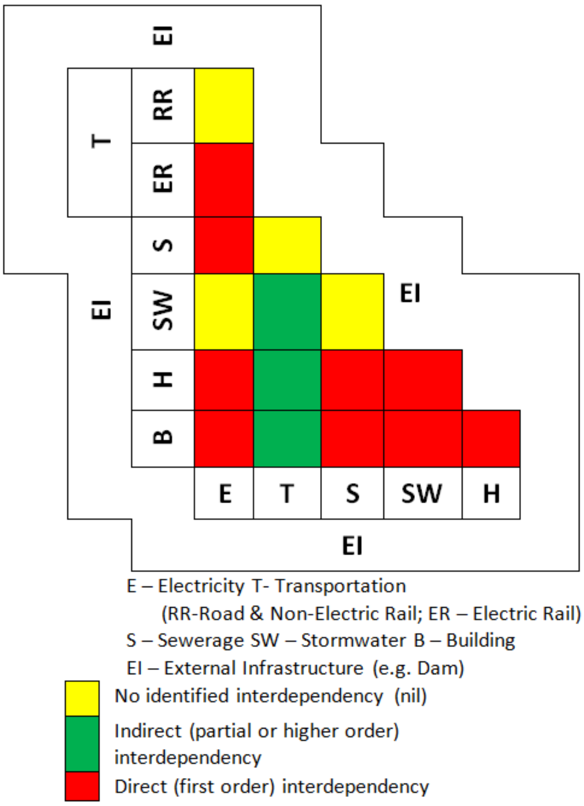


Figure 5.25 The critical infrastructure interdependency matrix

5.3.3 Climate Adaptation Strategies/Resiliency Measures

The analyses of vulnerabilities and interdependencies of critical infrastructure systems (CIS) were demonstrated in this study. The effects of having the infrastructures' components removed or disrupted by the January 2011 flood in Brisbane City were specifically examined. As the backbone of our society, it is essential to improve the climate resiliency of these critical infrastructures in such a way to maintain the interdependencies that exist among them.

The resilience of complex infrastructure systems has emerged as fundamental concern for system managers and other stakeholders (McDaniels *et al.* 2008). In Chapter 4, flood risk and climate adaptation capacity of the study area were assessed for disaster risk reduction and climate adaptation. The developed model was applied in identifying areas of low to very high flood risk and adaptation capacity to include disaster risk reduction measures and climate adaptation strategies (see Figure 4.45

and Table 4.3). The results of the analysis suggest of considering the following disaster risk reduction measures and/or climate adaptation strategies:

- Mitigation on areas of low flood risk or very high climate adaptation capacity;
- Mitigation to preparedness on areas of moderate flood risk and high climate adaptation capacity;
- Mitigation to response on areas of high flood risk and moderate climate adaptation capacity; and
- Mitigation to recovery on areas of very high flood risk and low climate adaptation capacity.

In this section, details of mitigating measures for disaster risk reduction and/or climate adaptation are outlined. We begin with electricity network and end up summarising the hierarchy of climate adaptation strategies across the critical infrastructure systems (CIS).

5.3.3.1 Electricity Network

Shared electricity network

Damage to shared electrical network infrastructure due to flooding disrupted the supply of electricity to large numbers of people including non-flooded premises (Arnold 2011, QFCI2012). Power was disconnected in flooded and selected non-flooded areas as a precautionary measure. Learning from the breakdown of some power stations (e.g. zone substations or bulk supply) due to flooding, it was recommended that electricity service providers should consider the following (Arnold 2011, Energex 2011, Sun 2011, and QFCI 2012) :

- Construction of critical electricity facilities above the defined flood level (DFL);

- Implementation of flood resilience measures such as moving critical equipment to higher locations, building bunds around substation, installing sump pumps, scaling vents and replacing all local power sockets below the DFL;

- Installation of connection points in the network for generators to supply electricity to non-flooded customers; and

- Electrical conduits below the applicable DFL should be sealed and water proofed to prevent floodwaters from flowing into them.

Customer-dedicated electricity network

Within the commercial and industrial premises, various customer-dedicated electrical assets were inoperative during and after the floods. Generator circuits located in building basements were isolated due to floodwaters and generated the risk of being exposed to live electricity if switched on (McLeod 2011, QFCI 2012). Due to these events, recommended adaptation and resiliency strategies included the following (de Lange 2011, McLeod 2011 QRA 2011, DEWS 2012, and QFCI 2012):

- Upgrading of generator circuits so that damaged parts can be isolated in any future flood;
- Electrical switchboards and substations should be placed on the higher level of the building basement;
- Non-flood resilient buildings should require permanent lifting devices for heavy equipment such as transformers and switchboards and 24-hour access to remove circuit breakers and sensitive equipment; and
- In new high rise building, the design of electrical equipment should be raised and located above the defined flood level (DFL).

The adaptation/resiliency measures for electricity network enumerated above should be designed to avoid human exposure from electromagnetic fields by considering the location, size and shape of the substation (DEWS 2012). To provide a new level of robustness, the electricity grid should utilize more dispersed generation sources, hydroelectric storage to store energy during periods of low demand, and greater generating capacity at times of peak demand (Collins *et al.* 2011).

The principal damage to the sewerage system caused by flooding was the result of failures of the electrical systems (generators and switchboards) which resulted in critical failures of sewerage treatment systems (Lewis 2011, QFCI 2012). To minimise future failures of the sewerage system, it was recommended to include in the resiliency strategies the installation of removable plant electrical systems in anticipation of the inundation (Clerke 2011, QFCI 2012), elevation of sewerage plant's electrical control panels, installation of back-up generators (Lewis 2011, QFCI 2012), and relocation of major power generators to higher ground (Belz 2011, QFCI 2012). Furthermore, in the construction and management of sewerage infrastructure it was also recommended to consider the risk and cost/benefit assessments to determine the vulnerability of electricity infrastructure to inundation and the need for relocation to higher ground (QFCI 2012), if practicable.

Electricity supply to health care infrastructure such as hospitals was at risk of being cut during the flood events, which would have necessitated the evacuation of all patients (Prado 2011, QFCI 2012). It was recommended that draft assessment criteria be included in the flood planning controls such that essential health care infrastructures should be able to continuously function during and immediately after a flood of a specified level of risk (QFCI 2012).

For other infrastructure operators who were dependent on electric power, some had implemented measures to protect their electrical system prior to flooding. For example, the Queensland Rail removed electrical points from rail yards to reduce the flood impacts to the railway's electrical system and ease of recovery after flood (Ford and Timmins 2011, QFCI 2012).

5.3.3.2 Road and Rail Networks

The transportation networks of Queensland are critical to the supply of goods and services. Over 9,000 km of road and 3,000 km of rail infrastructure were significantly affected by the 2010/2011 floods (QFCI 2012). To reduce the impacts of future inundation to road networks, it was recommended to upgrade flood plain transport infrastructure including the replacement of the concrete floodways and building new bridges with higher approaches above the DFL; however, these should be done with caution to reduce the consequential impact of future flooding upstream (Brown 2011, QFCI 2012).

Before the onset of the 2010/2011 floods, the following pre-emptive measures were applied and post-flood measures were recommended such that (Brown 2011, Ford 2011, Ford and Timmins 2011, Moore 2011, and QFCI 2012):

- Rail communication and signalling equipment rooms were raised one meter above the highest known flood to reduce the impacts of floods to rail network system;

- Pipes were installed under the railway line to prevent floodwaters from overflowing and causing scouring and moved rolling stock away from areas of possible flooding;

- For future rail network construction, it was recommended to design a 'flood-free' rail network above the defined flood level (DFL) and the utilisation of concrete pylons in the construction; or the design should be 'flood-proof' to endure floodwater flows;

- For heavy-haul rail infrastructure, the recommended flood response should include initiating a safety plan for large-scale disasters, purchasing of specialised meteorological device for operational decisions, moving locomotives and wagons to higher ground, and establishing a flood recovery taskforce.

Access to evacuation routes for some hospital and aged care facilities was similarly affected and completely lost due to inundation (QRA 2011, QFCI 2012). As earlier discussed, the vehicle access, including ambulance access, to and from the hospital was cut (Prado 2011a, 2011b, QFCI 2012). The event prompted a review of hospital access and consideration in investing in the installation of helicopter pad (Prado 2011a, 2011b, QFCI 2012). It was also recommended to draft assessment criteria to be included in the flood planning controls such that essential health care infrastructures should continuously function during and immediately after a flood of a specified level of risk (QFCI 2012).

For residential properties situated on low lying access routes and isolated by floodwaters, the situation gave little or no opportunity for residents to evacuate their families or remove belongings (Leighton 2011, QFCI 2012). It was recommended that assessment criteria should include flood planning controls that address both the prospect and impact of isolation or hindered evacuation (QFCI 2012).

5.3.3.3 Sewerage Network

Floods and backflows discharged untreated sewage through overflow relief structures into some residential areas, public parks and waterways into some private properties (QFCI 2012). To reduce the impacts of sewage discharge, pre-emptive measures such as sandbagging and blocking the entry points below previous flood levels to prevent floodwater causing backflow (Norman 2011, QFCI 2012), and lifting the low-lying pump stations to higher elevations to improve flood resilience (Smith 2011, QFCI 2012) were operationalised. A significant pre-emptive measure that facilitated flood resiliency for the sewerage infrastructure was the design of some pumping stations with a gravity-driven sewerage network which continuously provided service even without a functioning electrical system (Clerke 2011, QFCI 2012).

To alleviate public health issues from sewage discharge in anticipation of future flooding, the recommended strategies include (Belz 2011a, 2011b, Lewis 2011, and QFCI 2012):

- Modelling of peak wet weather flow in a sewer thirty (30) times the average dry weather flow through its network during extreme weather events;
- Construction of plant with reserve storage capacity for sewage and back-up generators with overflow relief structures and submersible pumps and motors;
- Sealing and pressurising the sewerage pipe network, redesigning the overflow relief gully caps, securing manhole covers, and installation and maintenance of sewage reflux valves to prevent stormwater flowing into the sewerage system; and
- Enhancing sewer planning in areas prone to flooding or stormwater flow.

Policy wise, it was further recommended to avoid the ‘common’ practice of directing or connecting stormwater to sewerage infrastructure (Lewis 2011, QFCI 2012) and conduct an educational program to raise public awareness that this practice was illegal and impeded the normal operation of sewerage infrastructure (QFCI 2012).

During the flooding, floodwaters may had been contaminated by sewage leaking from private on-site sewerage systems (e.g. septic tanks) and posed public health issues. Hence, it was recommended that criteria should be included as a requirement that the risk of leakage from private on-site sewerage systems during floods be minimised (QFCI 2012). To improve sewerage infrastructure resiliency, sewage reflux valves on private properties should be installed and properly maintained (Brumby 2011, QFCI 2012). Also crucially considered in the recommendation was the proposed involvement of distributor-retailers, developers, local governments, and property owners in the land use and infrastructure decision-making process (Lewis 2011, QFCI 2012).

5.3.3.4 Water Supply Network

Table 5.7 identified the highly and very highly vulnerable water supply network assets that can be potentially harmed in the future floods. Without the mitigation measures, the possible implications for water supply infrastructure include reduced security of supply and increased risk of fluvial flooding to water supply/treatment infrastructure (DEFRA 2011). As such, climate threats to water supply should be managed according to some lessons learned such as (Collins *et al.* 2011):

- To focus on new inter-disciplinary approaches by integrating social and economic solutions with the current engineering solutions;
- To implement distributed water systems rather than centralised water systems;
- Water recycling with conscious on energy implications of recycling water;
- Use of smart meters and intelligent pipework to reduce leakage, monitor turbid water, among others.

During the 2010/2011 floods, the supply of drinking water was maintained to meet the demands of consumers in south-east Queensland. However, this was constrained by the suspension of water treatment operations at Mt. Crosby and North Pine dam (QFCI 2011). To improve the quality of water during flood events specifically in the South East Queensland and Brisbane areas, Keller (2013) recommended an engineering modification by adding high quality water from the Advanced Water Treatment Plants (also known as water recycling plants) directly into the water treatment plant (i.e. Mt. Crosby Plant) rather than the Wivenhoe Dam. Accordingly, the advantages of this significant change include the following (Keller 2013):

- Generating up to 50% of its usual water production directly from the recycled water;
- “Dirty” river water could have been taken in and treated with the dilution from the purified recycled water;
- Pumping energy would be substantially less by not going to the dam, the high water quality could be maintained, and it would avoid losses through evaporation and infiltration from the dam.

5.3.3.5 Stormwater Network

Stormwater flooding and backflow flooding of the stormwater network caused basement damage to a number of high rise buildings and residential properties particularly in the low lying areas of Brisbane and the central business district (QFCI 2012).

Some future adaptation and resiliency strategies for stormwater infrastructure should consider the following (Bannan 2011a, 2011b, Cuerel 2011, Sun 2011, White 2010, Winders 2011, and QFCI 2012):

- Upgrade of older stormwater network system capacity to ensure desired services to the current population and level of development;
- Basements should be built with a higher level of flood immunity;
- Stormwater connections should be fully sealed to ensure that there is no probability of backflow into basements;

- Regular maintenance such as the need for culverts to be inspected for debris;
- Detention basins should be mowed and vegetation should be managed in natural ways;
- Use of remote-controlled vehicles with cameras to inspect pipe network located underground;
- Installation and/or retrofitting of backflow prevention devices to stormwater outlets such as flap gates, duckbill valves, and mechanically operated valves;
- Consideration of flood resilience of basements in the planning schemes;
- Areas susceptible to backflow flooding should be made aware of risk; and
- Stormwater systems which are part of council and state-owned roads and perform dual functions such as parklands that operate as overland flow paths should be designed and managed in reference to state and national policies.

In the upgrade and optimisation of existing stormwater networks, land development processes should ensure that there is no increase to the runoff downstream (QFCI 2012). Where land is built up with fill prior to the construction, it should be ensured that there should be no impacts to new development by way of ponding or runoff to adjoining properties (Kelly 2011, QFCI 2012).

5.3.3.6 Building Properties (Residential, Commercial, and Industrial)

Some residential properties were also isolated by floodwaters and some commercial properties (e.g. shopping centres) were inundated (Flegg 2011, QFCI 2012) by the 2010/2011 floods. For consideration in the future planning schemes, the minimum floor levels of habitable and non-habitable rooms of residential houses were recommended to build to a specified level of immunity (BCC 2011, QFCI 2012) and include consistency in height between the proposed building and the existing streetscape (ICC 2011, QFCI 2012). The design of residential buildings was suggested to include the use of water resistant materials of a non-structural nature (Brumby 2011, QFCI 2012). Setting a mandatory minimum freeboard level across the state or a higher freeboard in cases of high measure of uncertainty surrounding the estimated flood level (Reynolds 2011, QFCI 2012) was also recommended.

Other lessons learned from the 2010/2011 floods were that commercial buildings in low-lying precincts which were fitted with louvre windows for easy removal and partition walls built out of besser block (Cox 2011, QFCI 2012) were found to be flood resilient. Others benefited from the comprehensive evacuation plan coupled with building improvements such as walls constructed out of modern fibrous cement, use of acrylic water-based paint, raised electricity supply points and the use of flood resistant floor materials (White 2011, QFCI 2012). Some residential buildings built on the edge of a river were designed to ensure that built-in furniture were not placed in the downstairs area and that water resistant materials were used for the doors and walls of the lower levels (Scragg 2011, QFCI 2012).

The location of electrical assets such as switchboards and back-up power supplies was recommended to mitigate the effects of future floods (Queensland Development Code 2011, QFCI 2012). Conduits of electrical cables were recommended to be sealed and waterproofed (Sun 2011, QFCI 2012) to prevent stormwater from flowing into the building basements.

To significantly minimise the risk posed by flood to lives and properties, some local governments in Queensland currently operate “property buy-back” and “land swap” programs. The former involves the voluntary selling of privately owned properties which are prone to flooding to the local or state government and re-use for purposes other than residential (Lord Mayor’s Taskforce on Suburban Flooding 2005, BCC 2011, QFCI 2012). The land swap program, on the other hand, allows eligible property owners to “swap” their flood hazard land for land situated above the 2011 flood levels which was purchased by the local government (Simmonds 2011, QFCI 2012).

5.3.3.7 Hierarchy of critical infrastructures’ climate adaptation strategies

As a system, urban community and its critical infrastructures require a robust framework to foster the dimensions of system resilience (McDaniels *et al.* 2008). And there are numbers of methods that were developed for prioritising critical interdependent infrastructures to protect them from human threats and increase climate resiliency like the works of Wang *et al.* (2012), McDaniels *et al.* (2008), and Moteff (2005). To cope specifically with climate change, Australia established the Climate Change Adaptation Infrastructure Project which includes developing the standard climate change adaptation system (DEFRA 2011). This study, however, established the hierarchical framework of understanding climate resiliency for critical infrastructures in relation to actual extreme climatic events - the 2010/2011 floods in Queensland.

Figure 5.26 illustrates and summarises the hierarchy of interdependent infrastructure adaptation and resiliency actions operationalised during the 2010/2011 floods in Queensland. This inverted pyramid signifies that pre-emptive and post-flood measures to increase infrastructure adaptation and resiliency are graded from long-term measures (e.g. elimination) down to short-term measures (e.g. protection).

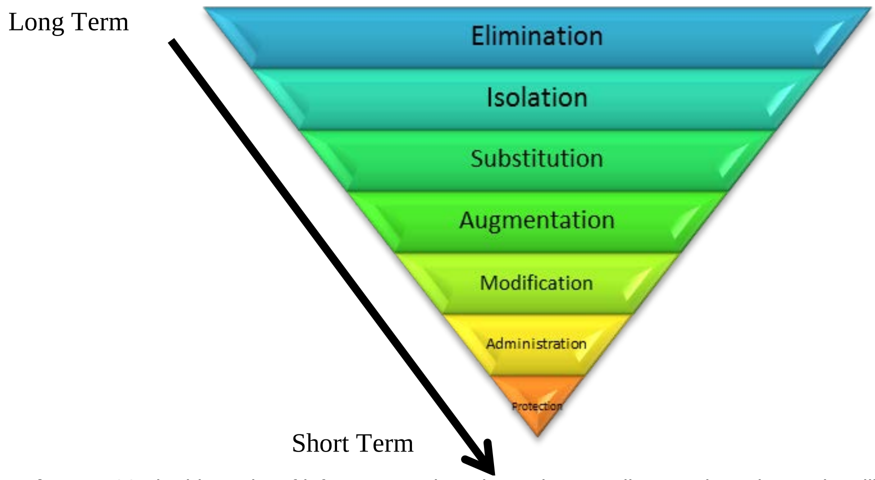


Figure 5.26 The hierarchy of infrastructure interdependency’s climate adaptation and resiliency measures in Queensland in response to 2010/2011 floods

Ideally, the most effective measure to mitigate flood risk is to eliminate the flood hazard. However, this was an expensive adaptation and resiliency strategy considering that the "removal" of infrastructure systems from flood hazard areas is a financially-exhaustive measure. The "property-buy-back" and "land swap" programs to "remove" the risk associated to flooding were the examples of risk elimination strategies.

When risk elimination was not a viable option, isolation was another adaptation and resiliency strategy option such as the installation of removable or hoisted electrical points from rail yards to reduce flooding impacts. When flood control measures involved the replacement of old infrastructure materials with flood resistant materials, this strategy substituted the infrastructure system to increase flood resiliency. When this substitution strategy could not be implemented, augmentation of new materials to the infrastructure system was another adaptation and resiliency strategy. An example was the installation of back-up generators to provide continuous electricity supply to non-affected areas and temporary mobile stations for the continuation of telecommunication services.

There were recommendations to redesign or modify infrastructure to withstand flood hazards. Examples were the proposed upgrade of old stormwater networks to accommodate the current needs of the population being served and the installation of additional pipes under the railway line to prevent floodwaters from overflowing (among others).

In a recommendation made by QFCI (2012), the implementation of flood mitigation policies in the future should consider some administrative and development measures such as the prohibition of direct connection of stormwater infrastructure to sewerage infrastructure to reduce inter-dependency. Whenever policy gaps emerged, policy amendments should adhere with the flood safety and resiliency standards.
When all the above pre-emptive strategies were not feasible, protective measures were adopted to increase infrastructure adaptation and resiliency. This was shown by using sandbags around sewerage pump stations, and blocking sewer entry points below previous flood levels. However, protective measures offered the least effective form of adaptation and resiliency strategy considering that this did not fully mitigate the flood risk.

5.4 Summary and Conclusion

Set within the four dimensions of critical infrastructure interdependency, this Chapter discussed the significance of GIS-based vulnerability assessment of critical infrastructure systems (CIS) both at single system level and interdependency or "system of systems" level. As a novel tool, this allowed identifying the vulnerabilities, interdependencies, and cascading effects of critical infrastructures due to January 2011 flood in Brisbane. Furthermore, climate adaptation strategies to increase the resiliency of CIS were also outlined in this Chapter.
The methodology presented in this Chapter will provide significant information to government-owned corporations, critical infrastructure systems managers, and other concerned stakeholders to:

- identify infrastructure assets that are highly critical;
- identify vulnerable infrastructures within areas of very high flood risk and low climate adaptation capacity;
- determine the level of flood risk and expected flood consequences to individual assets and integrated infrastructures;
- identify ways of reducing flood risk and extreme climate events; and
- prioritise disaster risk reduction (DRR) measures and climate adaptation (CA) strategies.

After having assessed the vulnerability and analysed the interdependency of the critical infrastructures, the final question addressed in this study focused on assessing the optimality of natural disaster risk reduction polices and/or climate adaptation strategies. This issue is fully discussed in Chapter 6.

Chapter 6

SPATIAL MODELLING OF NATURAL DISASTER RISK REDUCTION POLICIES WITH MARKOV DECISION PROCESSES

6.1 Introduction

Chapter 5 comprehensively discussed the flood disaster risk reduction measures and specific climate adaptation strategies for the urban community in general and critical infrastructures in particular. However, mitigating the devastating effects of floods to the community and critical infrastructures entails competing financial requirements from various levels of government. Hence, the main contribution of this Chapter is to provide the methods of assessing the financial optimality of disaster risk reduction measures or climate adaptation strategies by integrating the tool called Markov Decision Process(es) (MDP) with geographic information system (GIS). As comprehensively discussed in Chapter 2 (Literature Review), this approach has never been used in flood mitigation decision making in Australia and elsewhere.

The 2010/2011 floods in Queensland inflicted significant damages to government's critical infrastructures, private properties and businesses. In a joint report prepared by The World Bank and Queensland Reconstruction Authority (QRA) (2011), they observed the following (World Bank and QRA 2011):

- the adverse impacts of flooding to the State reached at least AU$15.7 billion;
- the amounts indicated by the federal and State governments for rebuilding the flood-affected areas were AU$5.6 billion and AU$2.1 billion, respectively; and
- the State governments' share includes the AU$3.9 billion expenditures from the Natural Disaster Relief and Recovery Arrangements (NDRAA).

The Disaster Management Act 2003 provides the legal basis for the Queensland's disaster management arrangements which had been established in three levels of hierarchy: the State Disaster Management Group, district disaster management groups, and local disaster management groups (Queensland Government 2011). The Queensland Reconstruction Authority (QRA) (2011) identified four disaster risk reduction measures that are being implemented in Queensland: mitigation, preparedness, response and recovery. Each of these measures has corresponding natural disaster related expenditures from the Commonwealth and State Governments which were instrumental in operationalising the Markov Decision Process.

Markov Decision Process (MDP) relies on theory to model feasible action with associated transition matrix containing the probabilities that performing the action in state *s* will move the system to state *s'* (Schapaugh and Tyre 2013). As a stochastic process, MDP is a decision-making model for finding optimum policy under certainty (White III and White 1989; Eun-Kim 1994; Dufour and Prieto-Rumeau 2014).

Several studies were conducted to model decision-making problems in different areas, such as finding optimum hydro-power production (Lamond and Boukhtouta 1996), maintenance policy of repairable power equipment (Tomasevicz and Asgarpoor (2009), inventory control problem for optimal ordering decisions (Ahiska *et al.* 2013), and natural resources conservation and management (Williams 2009).

In the field of disaster risk management, MDP was used in optimising open space for emergency response (Li *et al.* 2013). From the thorough review of related literature, the studies on optimising expenditures for natural disaster risk reduction have never been substantially explored. In this current study, a new way of dealing with uncertainty in the state transition function was introduced by using existing records on government expenditures for natural disaster risk reduction measures, social discounting factors, and total business loss during the January 2011 flood in the study area with the MDP environment. Thus, this study explored the novel approach of combining MDP with GIS to find the optimum natural disaster risk reduction policies that were implemented by the Commonwealth and State governments in Australia.

Further discussions on the research issues and the choice of MDP as analytical tool in this study are found in the subsequent sections and in Chapter 2 (Literature Review).

6.2 Research Methods

6.2.1 Setting the Markov Decision Processes (MDP) Algorithms

In principle, improving disaster risk reduction (DRR) measures and reducing the associated costs of climate adaptation strategies are the current top priorities for any flood-prone communities and critical infrastructure utilities. In an increasingly competitive financial environment, government expenditures should be spent optimally without losing the efficacy of the finest delivery of infrastructure service to communities. However, providing disaster-related services to urban community and management of critical infrastructures are confronted with many challenges in this highly competitive era: rising cost of disaster risk reduction measures, increasing demand on land and utilities, maintaining high levels of reliability and infrastructure services quality, and managing aged facilities, among others. Therefore, the fitness of the urban community and critical infrastructures can be measured when they can withstand the damaging effects of natural disaster like floods. It is of high importance that flood disruption should be maintained at the minimum; otherwise, lives, properties and business revenues would be positioned at very high risk from losing.

In this section, a spatial modelling to find optimal decisions for disaster risk reduction (DRR) was examined by setting up the problem as a Markov decision process (MDP). In general, MDP is a 4-tuple (S, A, R, T) mathematical framework where (Chan and Asgarpoor 2006):

S = a set of system states *s*;
A = a set of available actions *a*;
R = a set of state- and action-dependent immediate rewards or costs *R(s, a, s')*; and
T = a set of state- and action-dependent transition probabilities *T*(*s*, *a*, *s'*).

Following Chan and Asgarpoor's (2006) framework, the quantitative analysis of disaster risk reduction (DRR) measures was based on the assumption that the consequences of the measures employed are non-random. This suggests that for a given disaster risk reduction cost and the random flooding to urban community and critical infrastructures have no bearing on the frequency of implementing DRR. This study also assumed the process of stationary (i.e. time-independent); hence, the MDP's system states (i.e. past, present, and future) were considered independent from each other.

Figure 6.1 is the schematic representation of MDP used in the study. How each of the components operates is fully discussed in the subsequent sections.

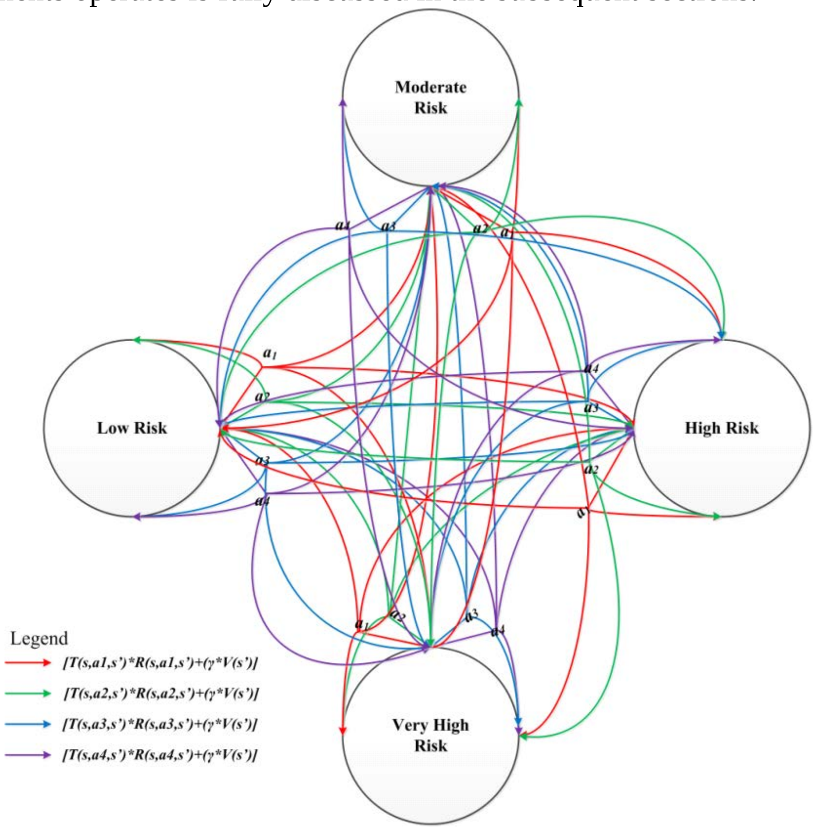


Figure 6.1 The schematic diagram of MDP used in the study (The red, green, blue, and purple arrows represent the combined transition probability, reward, & discounting factor for actions 1 (mitigation), 2 (preparedness), 3 (response), & 4 (recovery), respectively)

6.2.1.1 State variables

The flood risk state of the system (i.e. urban community and critical infrastructures) was examined with four random variables which correspond to the four levels of flood risk, i.e. $s \in S = \{1, 2, 3, 4\}$, where S is a finite state set. The first, second, third, and fourth levels are represented by the low flood risk condition level (s_1 = L), moderate flood risk condition level (s_2 = M), high flood risk condition level (s_3 = H), and very high flood risk condition level (s_4 = VH), respectively. Figure 4.36 from Chapter 4 was chosen to represent the state of the system considering that the figure provides the comprehensive spatial component of the study area's integrated infrastructure system.

Alternatively, this study can also use the climate adaptation capacity of the urban community and integrated infrastructure (see Figure 4.42 from Chapter 4) as the state of the system. However, this study opted to use Figure 4.36 as briefly described above.

6.2.1.2 Action variables

Four (4) decision variables were utilised in setting up the finite actions $a \in A(s)$ set at $s \in S$. These action variables include the four disaster risk reduction measures outlined in the Queensland State Disaster Management Plan 2011 (EMQ-DCS 2011): mitigation (a_1), preparedness (a_2), response (a_3), and recovery (a_4). The Emergency Management Queensland - Department of Community Safety (EMQ-DCS) (2011) defined these risk assessment components as follows:

> *Mitigation* is a risk treatment process that is linked to recovery that allows opportunity to build resilient communities through (1) the design and provision of more resilient new or updated infrastructures and services, (2) preparation of communities and response agencies and arrangements in place, (3) partnerships between sectors and community education to promote resilience activities, and (4) promotion of clear understanding of hazards, their behaviour and interaction with vulnerable elements;
>
> *Preparedness* is building capability and resilience to ensure that the community and all functions and services that are needed to better manage the consequences of a disaster. This may take in the form of community education and awareness, resilience, disaster management planning, training and education, exercises, and communication.
>
> *Response* involves the conduct of activities and appropriate measures necessary to respond to an event with immediate relief and support. Disaster response activities include:
>
> - Operational planning
> - Response
> - Declaration of disaster situation
> - State disaster coordination
> - Hazard analysis and modelling
> - Warnings

- Resupply
- Logistics support
- Evacuation management
- Search and rescue
- Emergency medical retrieval
- Offers of assistance
- Financial management and NDRRA cost substantiation
- Situational reporting
- Emergency supply
- Impact assessment
- Mass casualty and mass fatality management
- Debriefs, review and assessment

Recovery involves disaster relief by providing immediate shelter, life support and human needs to persons affected by, or responding to, a disaster. As part of the broader disaster recovery set out in the Queensland Recovery Guidelines, this phase of disaster management involves coordinated process of supporting affected communities in the reconstruction of physical infrastructure, restoration of the economy and the environment, and support for the emotional, social and physical wellbeing of those affected.

It was recognised in this study that these four phases of disaster management were not mutually exclusive and they overlap with each other; however, each had been used in the analysis as distinct action variable for the purpose of computational simplicity. Furthermore, this study also excluded the post-disaster assessment activities.

The quantitative analysis of the action variables for the MDP was based on the historical 12-year (1990-2002) government expenditure analyses prepared by the Australian Government Department of Transport and Regional Services (2004) as summarised in Tables 6.1 to 6.3.

Table 6.1 Total government expenditure by category 1990/91-2001/02

Year	Preparedness & Response		Relief/ Recovery		Mitigation		Other related expenditure		Aggregate Expenditure
	($M)	(%)	($M)	(%)	($M)	(%)	($M)	(%)	($M)
2001/02	433	55	274	35	63	8	21	3	791
2000/01	454	46	430	42	106	10	23	2	1014
1999/00	397	49	306	38	92	11	20	2	814
1998/99	340	47	294	41	73	10	13	2	720
1997/98	379	52	268	37	68	9	14	2	730
1996/97	296	57	152	29	61	12	10	2	519
1995/96	246	63	80	20	57	15	9	2	392
1994/95	230	64	68	19	55	15	9	2	362
1993/94	207	56	107	29	47	13	9	2	369
1992/93	182	59	88	29	29	9	8	3	306
1991/92	172	46	172	47	20	5	6	2	371
1990/91	167	32	334	63	20	4	6	1	527
Total	3503	626	2573	429	691	121	148	25	6915
Ave.	292	**52**	214	**36**	58	**10**	12	2	576

Source: Australian Government Bureau of Transport and Regional Economics (BTRE) 2002

Table 6.2 Total commonwealth expenditure by category 1990/91-2001/02

Year	Preparedness & Response		Relief/ Recovery		Mitigation		Other related expenditure		Aggregate Expenditure
	($M)	(%)	($M)	(%)	($M)	(%)	($M)	(%)	($M)
2001/02	0.1	0	194.0	89	15.2	7	13.8	6	223
2000/01	12.9	4	263.3	78	46.6	14	13.9	4	337
1999/00	13.4	7	123.8	67	40.9	22	11.7	6	189
1998/99	9.8	6	108.4	70	29.4	19	7.0	5	155
1997/98	8.5	4	146.9	77	28.9	15	6.9	4	191
1996/97	8.2	11	30.2	41	28.6	39	7.3	10	74
1995/96	8.4	17	4.6	9	29.1	59	7.1	14	49
1994/95	7.7	18	2.2	5	25.5	61	6.6	16	42
1993/94	7.9	18	5.2	12	24.1	55	6.4	15	44
1992/93	0.1	0	10.3	64	na		5.8	36	16
1991/92	0.1	0	59.0	91	na		5.7	9	65
1990/91	0.1	0	163.5	97	na		5.7	3	169
Total	77.2	85	1111.4	700	268.3	291	97.9	128	1554
Ave.	6.4	**7**	92.6	**58**	22	**24**	8	11	129

Source: Australian Government Bureau of Transport and Regional Economics (BTRE) 2002

Table 6.3 Total state and territory government expenditure by category 1990/91-2001/02

Year	Preparedness & Response		Relief/ Recovery		Mitigation		Other related expenditure		Aggregate Expenditure
	($M)	(%)	($M)	(%)	($M)	(%)	($M)	(%)	($M)
2001/02	433	76	80	14	48	8	6.7	1.2	568
2000/01	441	65	167	25	60	9	9.5	1.4	677
1999/00	383	62	183	29	51	8	8.0	1.3	625
1998/99	331	58	185	33	43	8	6.5	1.1	566
1997/98	371	69	121	22	40	7	7.3	1.4	539
1996/97	288	65	122	27	33	7	2.7	0.6	444
1995/96	237	70	75	22	28	8	2.0	0.6	341
1994/95	223	70	66	21	29	9	2.0	0.6	318
1993/94	199	62	101	31	23	7	2.4	0.8	323
1992/93	182	63	77	27	29	10	2.5	0.9	288
1991/92	172	56	113	37	20	7	0.6	0.2	305
1990/91	167	47	170	48	20	6	0.6	0.2	357
Total	3427	763	1460	336	424	94	50.8	10.3	5351
Ave.	286	**64**	122	**28**	35	**8**	4	0.85	447

Source: Australian Government Bureau of Transport and Regional Economics (BTRE) 2002

6.2.1.3 State transition probabilities

Given the phases of disaster risk management which are clearly defined in the Queensland State Disaster Management Plan 2011, the identification of the best available state transition probabilities for MDP was the next critical step considered in this study.

The underlying Markov processes that define the state transition probabilities for this study were associated with the average percentage of the government expenditures by category as presented in Tables 6.1 to 6.3. From Table 6.1 for example, it was assumed in this study that the probabilities that the combined government expenditure for Natural Disaster Relief and Recovery Arrangements (NDRRA) will be spent for mitigation (a_1), preparedness (a_2) and response (a_3), and recovery (a_4) are 10%, 52%, and 36%, respectively. Table 6.4 summarises the state transition probabilities used in the study. The 'other related expenditure' was excluded from the analysis because of its ambiguity into which this expenditure will be categorised.

Table 6.4 The state transition probabilities used in the MDP analysis

Action Variable	Transition Probability (*T(s, a, s')*)		
	Combined Government Expenditure	Commonwealth Government Expenditure	State/Territory Government Expenditure
Mitigation (a_1)	0.10	0.24	0.08
Preparedness (a_2) and Response (a_3)	0.52	0.58	0.28
Recovery (a_4)	0.36	0.07	0.64

The state transition probability was denoted in this study as *T(s, a, s')* being the probability of the current state *s* given an action *a* will lead to the future state *s'*. Through this definition, it was further assumed in this study that a particular state of the system (e.g. very high flood risk) will be reduced to a future state (e.g. high, moderate or low flood risk) if particular action (e.g. a_1, a_2, a_3 or a_4) will be implemented to mitigate the disaster. However, a caution should be stated upfront that the identified disaster risk management actions in this study cover all types of natural disasters and flood mitigation is only part of it.

6.2.1.4 Reward variables

Denoted in this study as *R(s, a, s')*, the reward variables of the MDP were based on the best available lost earnings by business impacted by the 2010/2011 floods. In January 2011 and six months after the natural disasters (i.e August 2011), the Chamber of Commerce and Industry Queensland (CCIQ) conducted surveys to determine the cost of damage and total lost earnings to business directly and indirectly affected by the Queensland floods. The pieces of information from Tables 6.5 and 6.6 were instrumental in the determination of the reward standardised rate (RSR).

Table 6.5 The total lost earnings for businesses impacted by the Queensland floods

Earning Bracket ($)	Directly Impacted (January 2011)		Indirectly Impacted (January 2011)		Directly Impacted (August 2011)		Indirectly Impacted (August 2011	
	%	RSR	%	RSR	%	RSR	%	RSR
1 – 4,999	1.8	0.25 (H)	2.3	0.33 (L)	3.2	0.22 (H)	-	0.08 (L)
5,000 – 9,999	9.1		5.4		1.6		-	
10,000 – 19,999	2.7		14.7		6.3		4.0	
20,000 – 49,999	20.0		27.1		12.7		4.0	
50,000 – 99,999	17.3		17.1		20.6		8.0	
100,000 – 499,999	25.4	0.25 (VH)	23.3	0.17 (M)	30.2	0.28 (VH)	60.0	0.42 (M)
500,000 – 999,999	8.2		3.9		7.9		8.0	
1,000,000 +	15.4		6.2		17.5		16.0	
Total	100	0.50	100	0.50	100	0.50	100	0.50

Source: Chamber of Commerce and Industry Queensland 2011

Table 6.6 The total lost earnings as a percentage of annual turnover for businesses impacted by the Queensland floods

Annual Turnover Classification (%)	Directly Impacted (January 2011)		Indirectly Impacted (January 2011)		Directly Impacted (August 2011)		Indirectly Impacted (August 2011	
	%	RSR	%	RSR	%	RSR	%	RSR
1 – 9	53.6	0.40	56.2	0.39	60.7	0.38	39.3	0.30
10 – 19	25.8	(H)	22.3	(L)	14.3	(H)	21.4	(L)
20 – 49	13.4	0.10	20.5	0.11	14.3	0.12	25.0	0.20
50 +	7.2	(VH)	0.9	(M)	10.7	(VH)	14.3	(M)
Total	100	0.50	100	0.50	100	0.50	100	0.50

Source: Chamber of Commerce and Industry Queensland 2011

The reward standardised rate (RSR) is referred in this study as the statistical measure of the rate of lost earnings by businesses impacted by the floods. This was computed by the following equation:

$$Reward\ Standardised\ Rate\ (RSR) = \left(\frac{\sum Lost\ Earning\ Rate\ for\ Flood\ Risk\ Level}{\sum Total\ Lost\ Earning\ Rate}\right) 100\% \,. \quad \text{Eq. 6.1}$$

In determining RSR, preliminary assumptions were considered. Table 6.5 classifies the total lost earnings of businesses into directly and indirectly impacted by the Queensland floods from the surveys conducted in January 2011 and August 2011. The indirectly affected earning brackets of \$1 – 99,999 and \$100,000 – 1,000,000+ were assumed to be within the areas of low flood risk level and moderate flood risk level, respectively. Within the same earning brackets classified as directly affected by floods, it was assumed to be within the areas of high and very high levels of flood risk. The same assumptions were applied to Table 6.6. However, the bracket assignments of the total lost earnings directly and indirectly affected by floods were based on the percentage of annual turnover.

Using the RSR in assigning the reward variable *R(s,a,s')* for MDP, this study considered the flood risk levels as the current states of the system with disaster risk reduction (DRR) measures as action variables and government expenditures as transition probabilities. For a given flood risk level (*s*) managed by an action variable (*a*) by using the government expenditure (*t*) to maintain or alleviate the current state of the system, three (3) possible example scenarios were assumed:

> **Scenario 1:** If the state of the system was assumed to maintain its current condition, then the system was considered to gain and maintain the current reward, either negative or positive final reward;
>
> **Scenario 2:** If the current state of the system was assumed to improve, then the system was considered to gain a positive reward; and
>
> **Scenario 3:** If the current state of the system was assumed to get worse, then the system was considered to gain a negative reward.

Given the current state of the system, assigning the final rewards to manage the disaster risk through the action variables that will lead to the future state of the system (*R(s,a,s')*) was considered dependent on the system's condition of recovery or loss of earnings. To mathematically operationalise the system of rewarding, the following examples are provided below.

Example 1

State of the System: Very High Flood Risk (VH)
Action Variable: Mitigation a_1
Transition Probability: 10%, 24% or 8%

In a very high flood risk condition (VH) with action variable a_1 using the corresponding transition probability from any government expenditure for example, four possible scenarios were generated. If the current state VH was assumed to remain VH in the future after action a_1 was implemented, a negative reward of -0.25 was maintained. If the current state was assumed to improve to high (H), the system was supposed to recover a 0.25 reward but because it lost 0.25 during the current state, then the system was expected to gain a 0 final reward. If the system was assumed to improve to moderate (M), the system was supposed to recover a 0.25 reward but because it lost 0.17 during the current state, then the system was expected to gain 0.08 as a positive final reward. If the system was assumed to improve to low (L), the system was supposed to recover the 0.25 reward but because it lost 0.33 during the current state, then the system was assumed to gain -0.08 as a negative final reward. The same principles were applied to action variables a_2, a_3, and a_4 and corresponding transition probabilities.

Example 2

State of the System: High Flood Risk (H)
Action Variable: Preparedness (a_2)
Transition Probability: 52%, 58%, or 28%

In a high flood risk condition (H) with action variable a_2 using the corresponding transition probability from any government expenditure, the following possible scenarios were generated. If the current state H was assumed to worsen to VH in the future despite after action a_2 was implemented, a double negative reward of -0.50 was expected: one from the high flood risk condition and the other one from very high flood risk condition. If the current state was assumed to remain high (H), a negative reward of -0.25 was maintained. If the system was assumed to improve to moderate (M), the system was supposed to recover a 0.25 reward but because it lost 0.17 during the current state, then the system was expected to gain 0.08 as a positive final reward. If the system was assumed to improve to low (L), the system was supposed to recover the 0.25 reward but because it lost 0.33 during the current state, then the system was expected to gain -0.08 as a negative final reward. The same principles were applied to action variables a_1, a_3, and a_4 and corresponding transition probabilities.

Example 3

State of the System: Moderate Flood Risk (M)
Action Variable: Response (a_3)
Transition Probability: 52%, 58%, or 28%

In a moderate flood risk condition (M) with action variable a_3 using the corresponding transition probability from any government expenditure, the following possible scenarios were generated. If the current state M was assumed to worsen to VH in the future despite after action a_3 was implemented, a double negative reward of -0.42 was expected: one from the moderate flood risk condition and the other one from very high flood risk condition. If the current state M was assumed to worsen to H in the future despite action a_3 was implemented, also a double negative reward of -0.42 was expected: one from the moderate flood risk condition and the other one from high flood risk condition. If the current state was assumed to remain moderate (M), a negative reward of -0.17 was maintained. If the system was assumed to improve to low (L), the system was supposed to recover the 0.17 reward but because it lost 0.33 during the current state, then the system was expected to gain -0.16 as a negative final reward. The same principles were applied to action variables a_1, a_2, and a_4 and corresponding transition probabilities.

Example 4

State of the System: Low Flood Risk ()
Action Variable: Recovery (a_4)
Transition Probability: 36%, 7%, or 64%

In a low flood risk condition (L) with action variable a_4 using the corresponding transition probability from any government expenditure, the following possible scenarios were generated. If the current state L was assumed to worsen to VH in the future despite after action a_4 was implemented, a double negative reward of -0.58 was expected: one from the low flood risk condition and the other one from very high flood risk condition. If the current state L was assumed to worsen to H in the future despite after action a_4 was implemented, also a double negative reward of -0.58 was expected: one from the low flood risk condition and the other one from high flood risk condition. If the current state L was assumed to worsen to M in the future although after action a_4 was implemented, also a double negative reward of -0.50 was expected: one from the low flood risk condition and the other one from moderate flood risk condition. If the current state was assumed to remain low (L), a negative reward of -0.33 was maintained. The same principles were applied to action variables a_1, a_2, and a_3 and corresponding transition probabilities.

6.2.1.5 Policy Iteration

For this study, the MDP was designed to find an optimal policy as a function of current states *S* and action variables *A*. The fundamental operation involved was the calculation of the expectimax value of the current state using the expected utility ($V^*_{(s)}$) under optimal action and the average sum of discounted rewards (Abbeel 2013). This operation utilised the Bellman equations and recursive definition of the expected utility to find the optimal policy π^*_s represented by the following relationships (Abbeel 2013 and Chang 2013):

$$V^*(s) = \max_{a \in A} V^a(s) \text{ at all } s \in S \qquad \text{Eq. 6.2}$$

$$V^a(s) = \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^a(s')] \qquad \text{Eq. 6.3.}$$

$$\pi^*_s = \operatorname{argmax} \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^a(s')] \qquad \text{Eq. 6.4}$$

where $\gamma \in (0, 1)$ is the discounting factor.

6.2.1.6 Discounting factors

From Eq. 6.4, the use of discounting factor $\gamma \in (0, 1)$ was based on a given time interval the value of money increases by a fraction *x*. Pfeiffer (2009) described this representation as the potential earning if the money were invested, i.e., one dollar now is worth $1 + x$ dollars at the end of one period or worth $(1 + x)^n$ dollars after n periods. This means that an extra dollar invested today will grow to more than a dollar tomorrow, a fact that according to Harrison (2010) reflected in positive market interest rates.

In this study, the selection of discounting rates from the work of Harrison (2010) and proposed to perform sensitivity testing of 3, 8 and 10% – accordingly, representing the weighted average riskless rate of return, the weighted average rate of return and rate of return for a riskier asset.
Figure 6.1 presented above summarises the MDP used in the study with four states and four action variables. The arrows from the figure signify the sixty four (64) combinations of solving the optimal policy by defining the future state of the system (*s'*) given the current states (*s*), transition probabilities, rewards, discounting rates, and expected utility.

6.2.2 Integration of Markov Decision Processes (MDP) with Geographic Information System (GIS)

The core problem of MDP is to find the optimal policy for the decision makers. In this study, it is about finding the optimal natural disaster risk reduction measures implemented by the State/Territory and Commonwealth governments of Australia. In the absence of the best available data for flood disaster risk management, natural disaster is defined in this Chapter as the one, or combination, of the following natural hazards: bushfire, earthquake, flood, storm, cyclone, storm surge, landslide, tsunami, meteorite strike, or tornado; excluding drought, frost and heat wave (DOTARS 2002). The advantage of using the "all hazards" approach is the development of consistent arrangements with future directions and will enhance Australia's capacity to deal with a wide range of emergencies (DOTARS 2002).
Figure 6.2 summarises the method of finding the optimum disaster risk reduction policy with MDP and GIS.

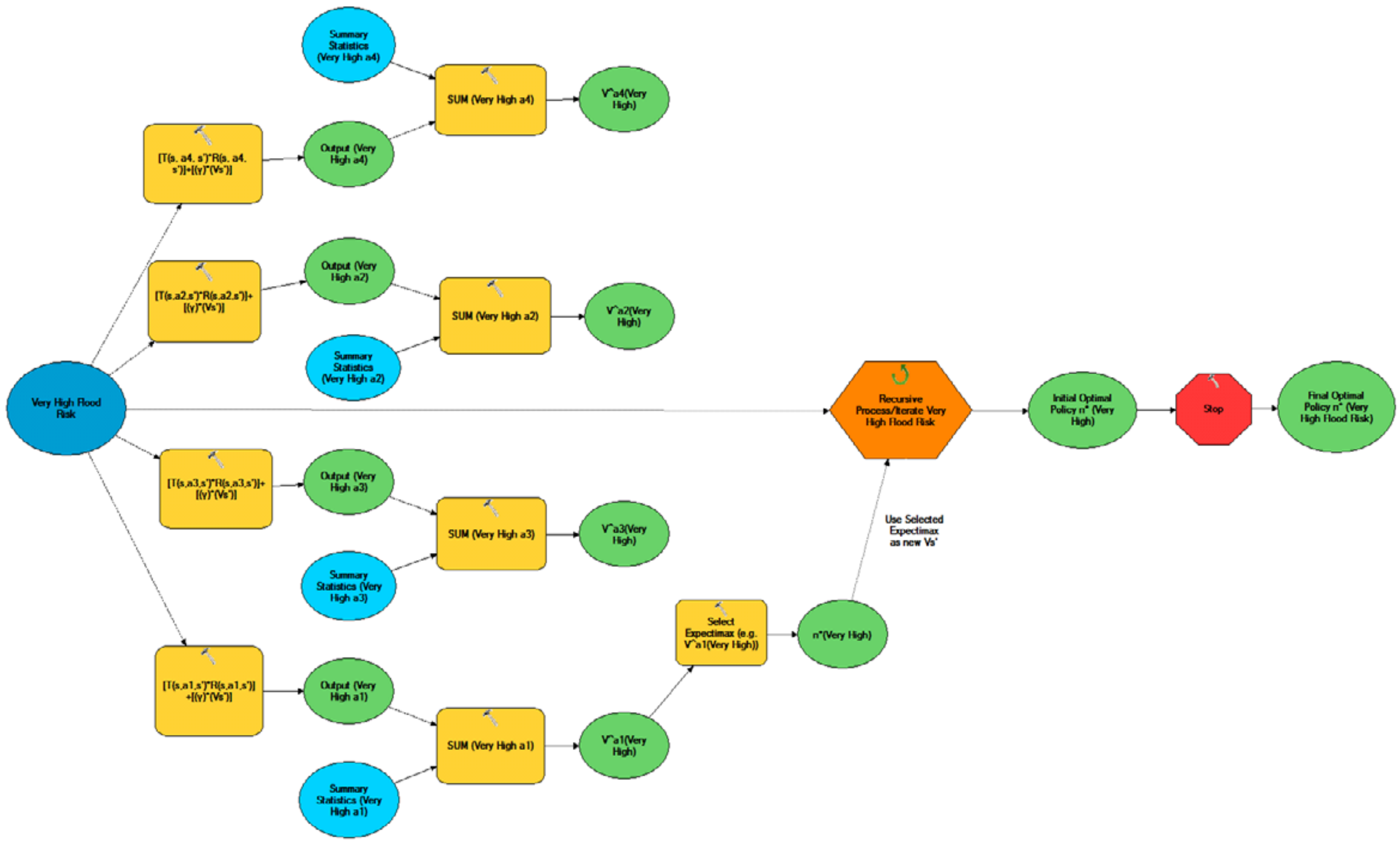


Figure 6.2 A sample schematic diagram of finding optimum natural disaster risk reduction policy with MDP and GIS

The process started by incorporating the MDP variables into the flood risk map (see Figure 4.38 from Chapter 4). Then Equations 6.2 to 6.3 were applied in calculating the expected utility values *V(s')* and finding the optimum disaster risk reduction policy. In using these equations, transition probability (e.g. $T(s,a_4,s') = 0.36$), reward variable (e.g. $R(s,a_4,s') = -0.25$), discounting factor (e.g. $\gamma = 0.03$), and initial expected utility *V(s')* (i.e. 0) were assigned appropriately according to the current state of the system (*s*), action variable (*a*), and future state of the system (*s'*). In assigning the MDP variables, each current state (e.g. very high) with corresponding action variable (e.g. a_4) was combined with the four levels of future state (e.g. low, moderate, high and very high risks). The sum of each output was calculated to select which of each level received the expected maximum utility value (expectimax). The chosen expectimax was then used as the new expected utility *V(s')*.

For each level, a recursive learning process was then operationalised until the succeeding expectimax values were found to be equal or nearly equal to the preceding expectimax values. Then the expectimax search was terminated at this instance and the optimum policy (π^*_s) was finally selected. The procedure has reached the convergence point of optimal policy (Pfeiffer 2009). In this study, the convergence of expected utility values was established at the fourth level of iteration.

6.3 Results and Discussions

This study applied the above algorithms to several conditions to test the sensitivity of changing or modifying MDP variables. Sensitivity tests were done in 36 scenarios as summarised in Appendix 3. Five hundred seventy six (576) maps were generated from the different MDP scenario analyses; however, only 24 maps are shown in this thesis representing scenarios 5, 17, and 29 (see Figures 6.3 to 6.6 and Appendices 4.1 to 4.8). Table 6.7 summarises the selected MDP scenarios presented in this Chapter.

Table 6.7 The summary of selected MDP scenarios presented in this Chapter

Scenario	Transition Probability *T(s,a,s')*	Discount Factor (γ)	Reward *R(s,a,s')*	Reward Survey Date
5	Commonwealth government expenditure	8%	Total lost earnings for businesses	January 2011
17	State government expenditure	8%	Total lost earnings for businesses	January 2011
29	Combined government expenditure	8%	Total lost earnings for businesses	January 2011

Given the above scenario information, the MDP models were mapped in GIS. The solution processes were made through the combination of attribute table calculation and Model Builder techniques in ArcGIS 10. For purposes of discussion and presentation in this Chapter, scenarios 5, 17, and 29 were selected. Common to these scenarios was the use of 8% discounting factor and the January 2011 total lost earnings for businesses in the MDP analysis. However, the dissimilarity of these scenarios was based on government expenditures: the first, second, and third set of scenarios were applied to test the Commonwealth government expenditure, State government expenditure, and combined government expenditure for disaster risk reduction, respectively. Figures 6.3 to 6.6 and Appendices 4.1 to 4.8 show the GIS-generated expected utility maps.

For MDP scenario 5, doing action 1(i.e. mitigation) given the current states of flood risk (i.e. low, moderate, high, and very high) with the expected future state of being either to remain or worsen to very high (VH) future state of flood risk, the expectimax value is -0.0931 (see Figure 6.3 upper left). Furthermore, doing actions 2 and 3 (i.e. preparedness and response) and 4 (i.e recovery), the expectimax values under the above conditions are -0.1781 and -0.0506, respectively (see Figure 6.3). From these values, the policy is said to be at its optimum for action 4 being the expectimax (i.e. -0.0506) is at the highest.

Doing actions 1, 2 and 3, and 4 given the current states of flood risk with the expected future state of being either to improve (e.g. from very high flood risk to high), remain (e.g. high to high), or worsen the state (e.g. from low or moderate flood risk to high), the expected utility values for each action are -0.2131, -0.4681, -0.0856, respectively. These findings show that the expectimax value of -0.0856 represents action 4 as the optimum policy (see Figure 6.4). Moreover, doing once again the four actions given the current states of flood risk with the expected future state of being either to improve (e.g. very high or high flood risk to moderate), remain (e.g. moderate to moderate), or worsen (e.g. low to moderate), the identified optimum policy was action 4 with expectimax value of -0.1150 (see Figure 6.5). Finally, Figure 6.6 shows that the optimum policy under this scenario is also action 4 with expectimax value of -0.1724.

The consistency of these findings shows that the Commonwealth government expenditure had been utilised optimally to focus on recovery from natural disaster. This finding agrees with the impression that as soon as a disaster is declared, federal funds are made available to rebuild and re-make flooded communities to "pre-disaster" conditions (Hussey and Pittock 2013). However, the State government utilised its disaster risk management expenditure in a different way. Bringing the current states of flood risk to either very high, high, moderate, or low flood risk using the four action variables generated expectimax values of -0.0579, -0.0979, -0.1315, and -0.1971, respectively (see Appendices 4.1 to 4.4). These values represent action 1 (i.e. mitigation) as the optimum policy. In interpreting MDP scenario 17, this implies that the State government expenditure was optimally utilised to focus on mitigation measures to reduce the severity of natural disasters.

When the Commonwealth and State government expenditures were combined, the expectimax values also exemplified action 1 as the optimum policy as shown in Appendices 4.5 to 4.8. MDP scenario 29, together with MDP scenario 17, showcase and confirm an expected result of having action 1 (i.e. mitigation) as the optimum policy. In Australia, the governments considered flood mitigation as one of the important aspects of flood disaster risk reduction measures as comprehensively provided in the four recent reviews of flood mitigation and adaptation. These inlcude the Queensland Floods Commission of Inquiry, Brisbane City Council's Flood Response Review, Inquiry into Flood Mitigation Infrastructure in Victoria, and the Victorian Floods Review (Hussey and Pittock 2013).

As such, the results from the MDP scenarios will implicate on how natural disaster risk reduction funds will be optimally used in the future and will give reflections on the effective implementation of flood mitigation given the government expenditures. The presented application of Markov Decision Processes (MDP) is a novel optimisation model for flood risk management. A Markov process-based methodology allows a computationally feasible integration of a complex physical model with economic variables (Freier *et al.* 2011). In this study, the flood risk model was integrated with economic variables (e.g. government expenditures, discounting factors, and total lost earnings for businesses) to find the optimal natural disaster risk reduction policy within a GIS environment. In the application to critical electricity infrastructure, for example, the optimum policy (e.g. maintenance) maximises benefits (Chan and Asgarpoor 2006). Assuming that the urban community and the infrastructure system are in a very high (VH) flood risk state under MDP scenarios 1, 2, 4, 5, 6, 8, 9, 10 12 (see Table 6.9) to shift its policy from recovery to mitigation, the results could reduce the severity of natural disasters. There is evidence that the estimated benefits of flood mitigation measures in terms of tangible savings are substantial such as (BTRE 2002):

- Land use planning is estimated to save around $29 million in direct and indirect costs under a 1 per cent AEP flood;
- Altering the way infrastructure is designed and constructed can be a very cost-effective mitigation measure; and
- Community awareness and preparedness of businesses saved more than 80% of potential flood damage.

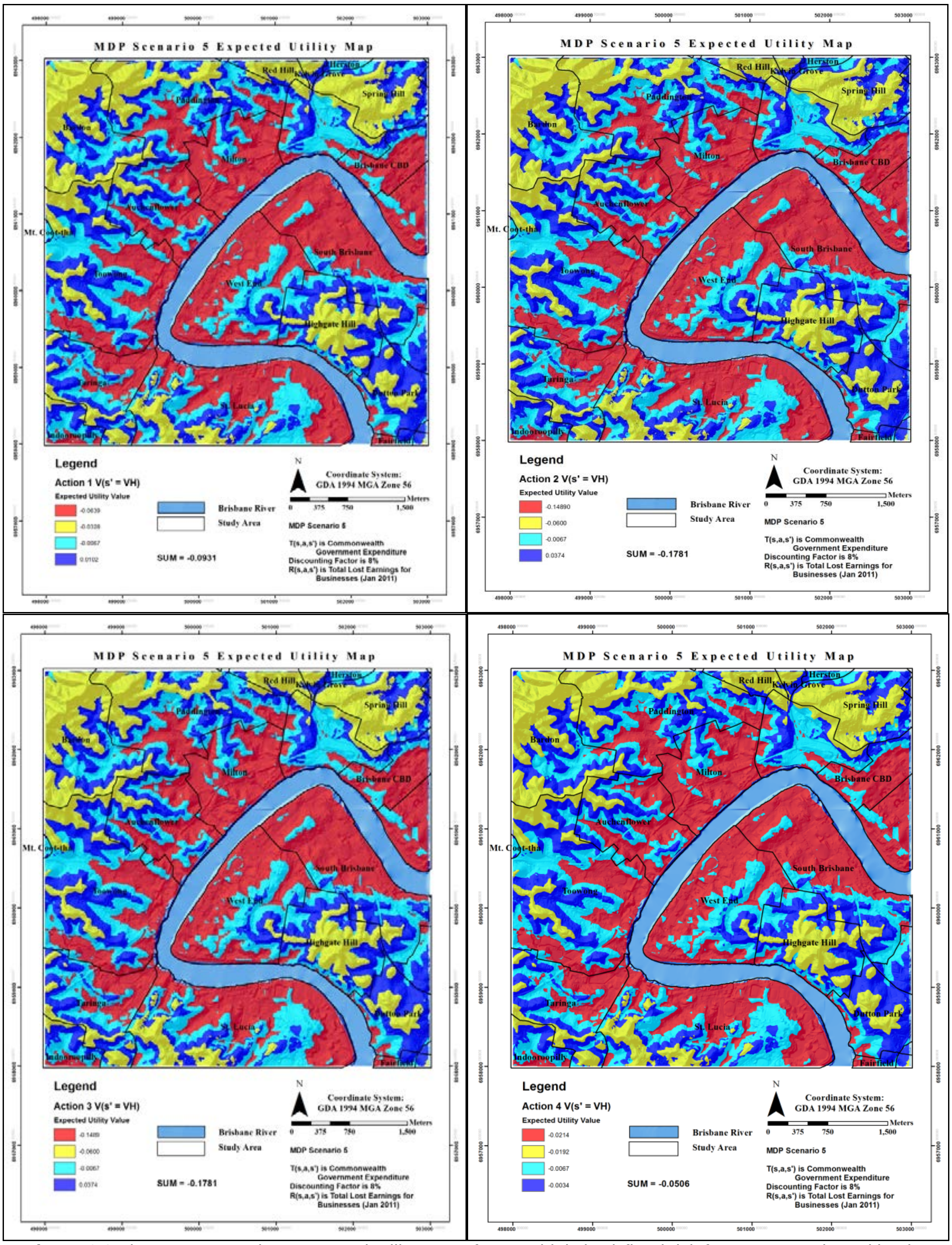


Figure 6.3 The MDP scenario 5 expected utility maps for very high (VH) flood risk future state using mitigation (upper left), preparedness and response (upper right and lower left), and recovery (lower right) action variables

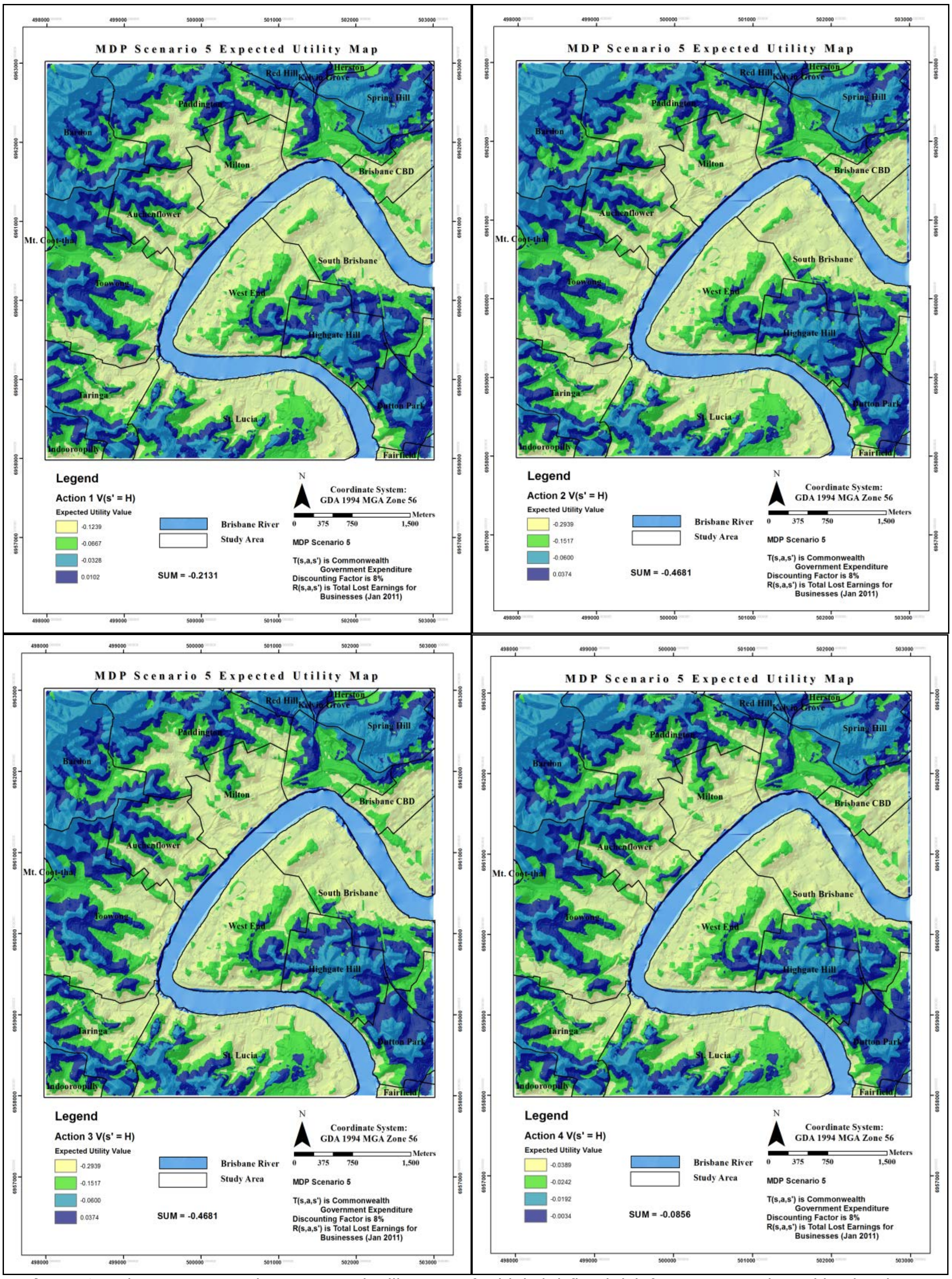


Figure 6.4 The MDP scenario 5 expected utility maps for high (H) flood risk future state using mitigation (upper left), preparedness and response (upper right and lower left), and recovery (lower right) action variables

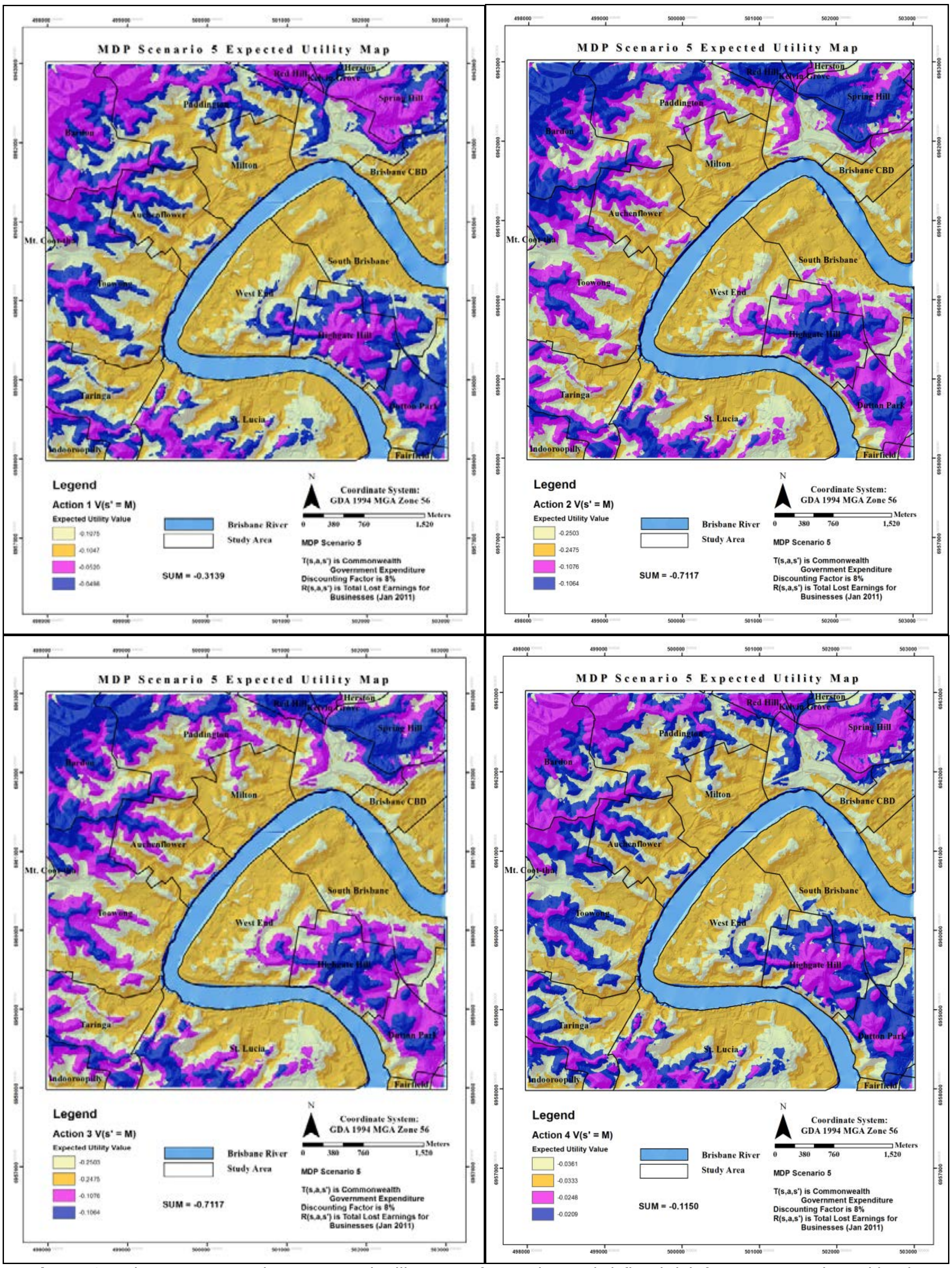


Figure 6.5 The MDP scenario 5 expected utility maps for moderate (M) flood risk future state using mitigation (upper left), preparedness and response (upper right and lower left), and recovery (lower right) action variables

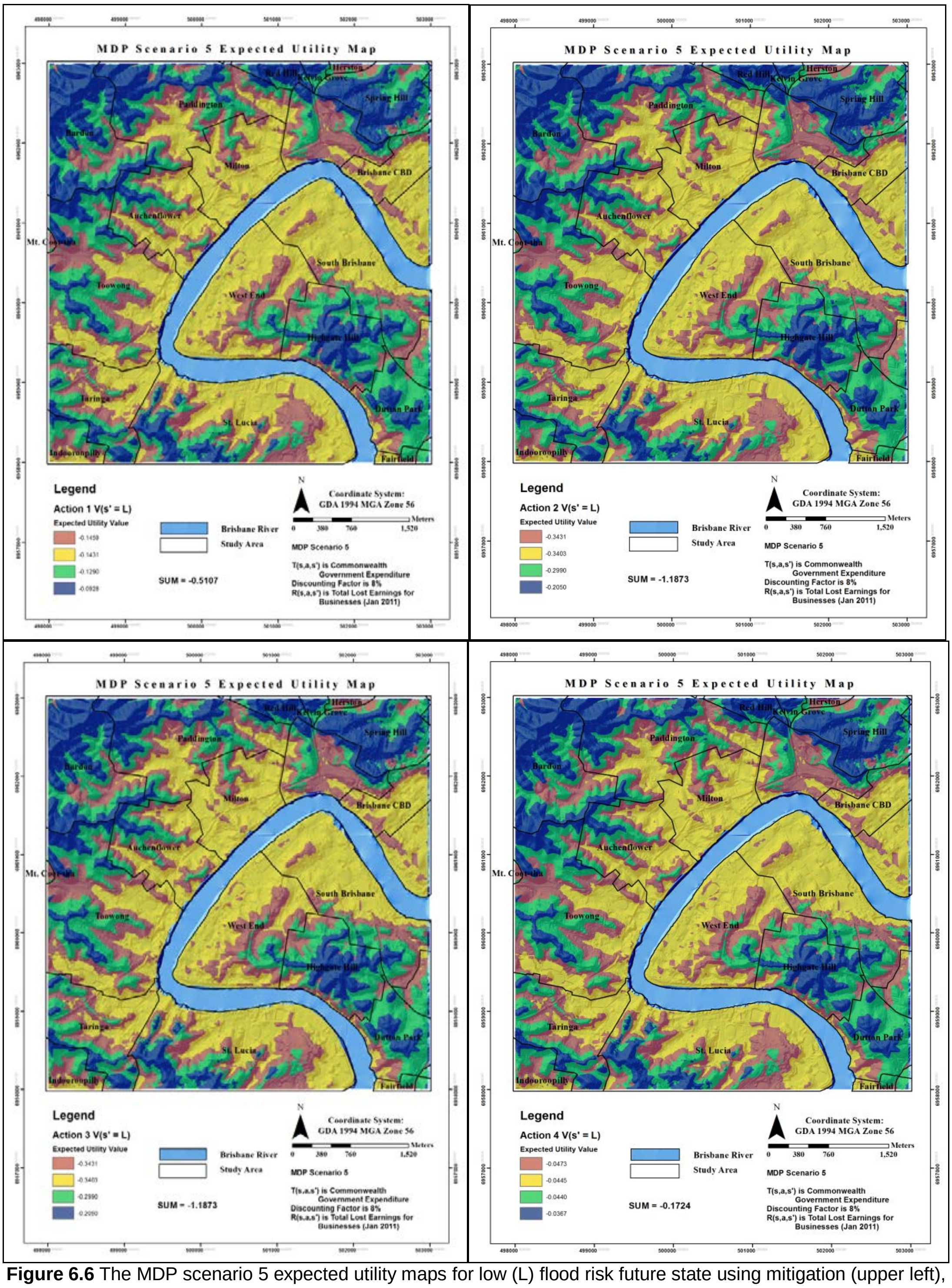


Figure 6.6 The MDP scenario 5 expected utility maps for low (L) flood risk future state using mitigation (upper left), preparedness and response (upper right and lower left), and recovery (lower right) action variables

Furthermore, the identification of optimum policies can also be ranked using the expectimax values. MDP 5 scenarios demonstrate that recovery (a_4) is priority over mitigation (a_1) then preparedness and response (a_2 and a_3). On the other hand, MDP 17 scenarios exhibit a pattern of priority such that mitigation (a_1) is priority over preparedness and response (a_2 and a_3) then recovery (a_4). For MDP 29 scenarios, mitigation (a_1) is priority over recovery (a_4) then preparedness and response (a_2 and a_3). These observations are summarised in the following matrix.

Table 6.8 The pattern of disaster risk reduction optimum policy

MDP Scenario	Pattern of Optimum Policy
5	$a_4 > a_1 > a_2$ and a_3
17	$a_1 > a_2$ and $a_3 > a_4$
29	$a_1 > a_4 > a_2$ and a_3

Table 6.9 is provided to summarise the expectimax values and corresponding optimum policies across the 36 MDP scenarios. The results of the MDP analysis were found consistent whether the assigned reward variables were based on January 2011 and August 2011 surveys. However, the readers are cautioned in interpreting the values and using the optimum policies considering that the MDP variables were limited based on the following:

- The MDP analysis was mainly based on natural disaster risk management expenditures by the governments and not the actual risk reduction measures;
- The reward and discounting factors were established on the basis of existing literature with corresponding assumptions as comprehensively presented above.

Table 6.9 Summary of the expectimax values and optimum policies across the MDP scenarios

Scenario	Expectimax Value of Future Flood Risk (Vs')				Optimum Policy
	VH	*H*	*M*	*L*	
1	-0.0274	-0.0624	-0.0918	-0.1492	Recovery (a_4)
2	-0.0599	-0.0529	-0.0886	-0.1628	Recovery (a_4)
3	-0.0479*	-0.0641	-0.1089	-0.0963	Mitigation (a_1)* and Recovery (a_4)
4	-0.0562	-0.08	-0.101	-0.1444	Recovery (a_4)
5	-0.0506	-0.0856	-0.115	-0.1724	Recovery (a_4)
6	-0.0855	-0.0785	-0.1142	-0.1884	Recovery (a_4)
7	-0.0702*	-0.0864	-0.1312	-0.1186	Mitigation (a_1)* and Recovery (a_4)
8	-0.083	-0.1068	-0.1278	-0.1712	Recovery (a_4)
9	-0.0629	-0.0979	-0.1273	-0.1847	Recovery (a_4)
10	-0.099	-0.092	-0.1277	-0.2019	Recovery (a_4)
11	-0.0820*	-0.0982	-0.143	-0.1304	Mitigation (a_1)* and Recovery (a_4)
12	-0.0972	-0.121	-0.142	-0.1854	Recovery (a_4)
13	-0.0313	-0.0713	-0.1049	-0.1705	Mitigation (a_1)
14	-0.0685	-0.0605	-0.1013	-0.1861	Mitigation (a_1)
15	-0.0226	-0.0722	-0.1234	-0.109	Mitigation (a_1)

Scenario	Expectimax Value of Future Flood Risk (Vs')				Optimum Policy
	VH	*H*	*M*	*L*	
16	-0.0643	-0.0915	-0.1155	-0.1651	Mitigation (a_1)
17	-0.0579	-0.0979	-0.1315	-0.1971	Mitigation (a_1)
18	-0.0977	-0.0897	-0.1305	-0.2153	Mitigation (a_1)
19	-0.0456	-0.0952	-0.1464	-0.132	Mitigation (a_1)
20	-0.0949	-0.1221	-0.1461	-0.1957	Mitigation (a_1)
21	-0.0719	-0.1119	-0.1455	-0.2111	Mitigation (a_1)
22	-0.1132	-0.1052	-0.146	-0.2308	Mitigation (a_1)
23	-0.0577	-0.1073	-0.1585	-0.1441	Mitigation (a_1)
24	-0.1111	-0.1383	-0.1623	-0.2119	Mitigation (a_1)
25	-0.0392	-0.0892	-0.1312	-0.2132	Mitigation (a_1)
26	-0.0856	-0.0756	-0.1266	-0.2326	Mitigation (a_1)
27	-0.0283	-0.0903	-0.1543	-0.1363	Mitigation (a_1)
28	-0.0803	-0.1143	-0.1443	-0.2063	Mitigation (a_1)
29	-0.0723	-0.1223	-0.1643	-0.2463	Mitigation (a_1)
30	-0.1221	-0.1121	-0.1631	-0.2691	Mitigation (a_1)
31	-0.057	-0.119	-0.183	-0.165	Mitigation (a_1)
32	-0.1186	-0.1526	-0.1826	-0.2446	Mitigation (a_1)
33	-0.0899	-0.1399	-0.1819	-0.2639	Mitigation (a_1)
34	-0.1414	-0.1314	-0.1824	-0.2884	Mitigation (a_1)
35	-0.0722	-0.1342	-0.1982	-0.1802	Mitigation (a_1)
36	-0.1389	-0.1729	-0.2029	-0.2649	Mitigation (a_1)

Interestingly, the results presented in Tables 6.8 and 6.9 are particularly useful in determining the funding priorities of the Australian governments in terms of natural disaster risk reduction. MDP scenarios 1 to 12, for example, give an indication that the Commonwealth government expenditure focused on recovery which comes in agreement with the findings of Insurance Australia Group (IAG). Accordingly, its spending on mitigation initiatives represents around only 3 per cent of what it spends on post-disaster recovery and reconstruction (IAG 2013). The Productivity Commission also highlighted that compared to the $6.7 billion spent on disaster recovery over the last 6 years, only $0.18 billion was spent on disaster mitigation (Milne 2013). It was further estimated that 80% of post-disaster relief and recovery expenditures are outlaid by the Australian government (Deloitte Access Economics 2013).

The implications of the above findings require the need to re-examine the sufficiency of cost associated with the natural disaster risk mitigation as optimum policy implemented by the State government (see MDP scenarios 13 to 24 for examples). If full consideration be given to prioritise pre-disaster mitigation activities, it will reduce the public money spent on post-disaster recovery in the future and would generate budget savings in the order of $12.2 billion for all levels of government (Deloitte Access Economics 2013). If the combined government expenditure on natural disaster mitigation (see MDP scenarios 25 to 36) will be successfully implemented, the future cost of natural disaster relief and recovery could be reduced by 50% by 2050 with a Benefit-Cost Ratio (BCR) of around 1.25 (Deloitte Access Economics 2013).

Based on the above findings, there was a clear indication that the results of the MDP analysis in this study established an agreement with the previous economic analysis.

6.4 Summary and Conclusion

This Chapter started with the identification of the Markov Decision Processes (MDP) variables. These include the flood risk states, action variables, discounting factors, and reward variables which were generated from the initial flood risk analysis and available literature. These variables were integrated in the GIS environment through the Model Builder with ArcGIS 10. Combined with the attribute table calculation technique, the expected utility values for each flood risk level and the maximum expected utility (expectimax) values were generated. The optimum policy for natural disaster risk management was then identified based on the highest expectimax value. Results revealed that the Commonwealth government optimised the use of its natural disaster risk expenditure to recovery while the State government focused on mitigation.

The use and integration of MDP with GIS in finding the optimum policy will provide benefits to natural disaster risk managers and decision-makers in a variety of ways such as:

1. allocation of optimum expenditure for natural disaster risk management;
2. visual representation MDP-based flood risk scenarios given the current states and expected future states; and
3. finding optimum natural disaster risk reduction policy for decision-making and implementing alternative courses of action.

The methodology presented in this study allowed a spatial representation and computationally feasible integration of a complex flood disaster risk model with government expenditures and business earnings. The insights from this integrated approach emphasised the viability of finding optimum expenditures, and the need to re-examine if necessary, in implementing natural disaster risk reduction policies and climate adaptation strategies.

Finally, the findings of the MDP analysis illustrated an opportunity to empirically elucidate how the Australian governments spent its natural disaster risk reduction budget. Apparently, there was a clear indication and greater agreement that mitigation is the optimum policy to reduce the risk from natural disasters; however, this finding was inconsistent when looking at the Commonwealth government budget only. The MDP scenario analysis and economic analysis reached an agreement on this regard.

Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This study aimed to investigate the vulnerability and interdependency of urban community's critical infrastructures using an integrated approach of flood risk and climate adaptation capacity assessment in conjunction with newly developed spatially-explicit analytical tools. To achieve this goal, three specific objectives detailed in Chapter 1.3 were addressed in Chapters 3 through 6. This last Chapter presents the summary of the findings and offers conclusions and recommendations for future research works.

7.2 Summary of Findings

The study provided novel knowledge and fresh insights on natural disaster risk assessment of an urban community and its critical interdependent infrastructures. This yielded new information on how the assessment was made possible through the integration of spatial analytical tools, artificial intelligence (i.e. Self-Organising Neural Network (SONN), network theory, and optimisation technique like the Markov decision processes (MDP).

The study from ***Chapter 3*** served as the "gateway" for the modelling of flood risk and climate adaptation capacity. It scoped the spatial analytical tools that allowed the transformation and standardisation of flood risk and climate adaptation capacity indicating variables sourced in various data representations. The major outputs were the generation of 5m gridded indicating variables representing hazard, physical vulnerability, social vulnerability, and exposure indicating variables of the urban community and its critical infrastructures.

From the analysis in ***Chapter 4,*** the development of flood risk and climate adaptation capacity metrics was detailed. The following were the major findings:

- There was an inverse relationship between the degree of flood risk and climate adaptation capacity of the studied urban community by infrastructure category. The areas occupied with very high flood risk metrics were found to have low climate adaptation capacity metrics. However, caution should be emphasised that representing flood risk with climate adaptation capacity or vice versa could give misleading results. This is because the areas being occupied with very high flood risk are larger than the areas being occupied by low adaptation capacity across infrastructure categories;
- The majority of the study area revealed negative climate adaptation capacity metrics (minimum of -22.84 to < 0) which indicate that the resources (e.g.

socio-economic) are not enough to increase climate resiliency of the urban community and its critical infrastructures;

- The developed metrics were used to identify disaster risk reduction measures and/or climate adaptation strategies as follows:
    - Mitigation on areas of low flood risk or very high climate adaptation capacity
    - Mitigation to preparedness on areas of moderate flood risk and high climate adaptation capacity
    - Mitigation to response on areas of high and moderate climate adaptation capacity; and
    - Mitigation to recovery on areas of very high flood risk and low climate adaptation capacity.
- Finally, the results from the analysis allowed generating a model newly identified in this study as *flood risk-adaptation capacity index-adaptation strategies (FRACIAS) linkage model*.

The methods used in assessing the vulnerability of critical infrastructures for interdependency analyses were outlined in ***Chapter 5***. The analyses were performed into two levels: single or individual infrastructure level and interdependency level. For the single system level, the notable findings were:

- Electricity supplies were disrupted along the 627km (75%) and 212km (25%) transmission lines in the North West and South East portions of the study area during the January 2011 flood;
- Approximately 170km (47%) of road and 2.5km (38%) of rail networks were identified to be highly vulnerable within areas of very high flood risk and low adaptation capacity. Using these information in emergency evacuation management, the evacuation route analysis revealed that 21km and 20.7km travel distances were calculated to travel to the first evacuation centre (i.e. RNA Show Grounds) and second evacuation centre (i.e. QEII Stadium), respectively;
- In the water supply infrastructure analysis, turbid water may found to flow along 246km (56%) water distribution lines;
- Sewerage networks' main trunk, reticulation and pressure rising system were affected during the January 2011 flood by 91% (33km), 78% (32km), and 81% (16km), respectively.
- Finally, 87km (19%) of stormwater pipes were also affected by the flood event.

For the interdependency level, the following were the major findings:

- The direct or first order interdependency of electricity infrastructure with sewerage infrastructure positioned the latter into critical failure due to the failure of the former infrastructure. This interdependency was also found to propagate to health care facilities;
- The higher order interdependency was also represented showing the ripple effects of electricity failure down to inaccessibility of roads for emergency evacuation;
- The co-location representation of highly vulnerable stormwater and sewerage networks provided an analytical tool for monitoring the "illegal" connections between these infrastructures;

- In general, the infrastructure interdependencies of the urban community's critical infrastructures were categorised into direct, indirect, and nil interdependencies;
- The hierarchy of interdependent infrastructure adaptation and resiliency actions during the 2010/2011 floods in Queensland were identified to have an inverted pyramid structure such that pre-emptive and post-flood measures were graded from long-term measures (e.g. elimination) down to short-term measures (e.g. protection).

Finally, the study in ***Chapter 6*** outlined the methods used in finding the optimum disaster risk reduction policies with Markov Decision Processes (MDP). The significant findings revealed that the Australian Commonwealth government expenditure had been utilised to focus on recovery from natural disaster while the State government focused on mitigation. However, when commonwealth and state government expenditures for natural disaster risk reduction were combined, mitigation was found to have been the optimum expenditure policy. These findings were consistent across different MDP scenarios. The patterns of disaster risk reduction optimum natural disaster risk reduction policy was also noted by ranking the MDP's expectimax values. The findings of the MDP analysis illustrated an opportunity to empirically elucidate how the Australian governments spent its natural disaster risk reduction budget. Apparently, there was a clear indication that mitigation was the identified optimum policy to reduce the risk from natural disasters; however, this finding was inconsistent when looking at the Commonwealth government budget only. The MDP scenario analysis and economic analysis reached an agreement on this regard.

7.3 Conclusions

This research proved the hypothesis that "*Spatially explicit flood risk and climate adaptation capacity models can provide sets of information that are useful in planning and developing strategies from the potential effects of extreme flood event to the physical assets (human settlement and critical infrastructure systems) of an urban community*.

In the aspects of technical contribution, usefulness, and innovation, the findings from this study were equal to or exceeded all other studies reported in the literature due to the following reasons:

- The analyses set a comprehensive techniques from transforming and standardising flood risk and climate indicating variables to generating flood risk and climate adaptation capacity metrics and finding optimum natural disaster risk reduction policy with the usage of geographic information system and remote sensing;
- The network model of evaluating the interdependency of critical infrastructures rendered suitable for analysing large-scale interdependent infrastructures;
- The study was able to systematically analyse the linkage amongst the different drivers and factors exposing an urban community and critical interdependent infrastructures to extreme climatic event. This showed a great promise on finding ways on how to increase its climate resiliency;

- Through this novel methodology, this study revolutionised the old compartmentalised methods of assessing the flood risk and climate adaptation capacity of flood plain areas worsened by the absence of critical infrastructure interdependency in the geographic analyses; and
- Finally, the nexus between the descriptive and prescriptive modelling techniques with GIS-enabled application to climate risk assessment is the main contribution of this thesis to the body of knowledge.

A number of advantages can be generated from the above studies. The first thing is the feasibility of integrating critical infrastructure interdependency analysis in setting up a comprehensive floodplain management system. This will significantly help in reducing the number of properties and the built environment being exposed to extreme climatic event such as flood. Furthermore, in a highly competitive environment where financial resource is scarce, natural disaster risk reduction expenditures should be optimally used. In agreement with the established economic principle, the Markov Decision Process (MDP) analysis has shown a great promise of finding the optimum disaster risk reduction policy. This approach will greatly benefit households, businesses, and different levels of government in finding “best” solutions to reduce life, insurance, business earnings, and property losses from natural hazards and maximise long-term benefits.

In relation to other studies such as those conducted by Balica *et al*. (2013), the parametric model used in this study is constrained on the availability of hazard, vulnerability, and exposure datasets. The advantage of using this approach is the simplified way of integrating flood risk, climate adaptation capacity, and adaptation strategies which had been, apart from being understood as a complex system, treated separately in the past. However, this study can only be applicable on small study areas with datasets of high level of accuracy. Although applicable in the regional and national scales, the resolution and accuracy of datasets can be a significant issue and the tasks involved (e.g. utility network modelling and critical infrastructure interdependency analysis) can be enormous considering that the analysis involved is up to point geographic level. Furthermore, taking high resolution datasets involved a considerable amount of financial resources. Section 7.4 below provides other limitations of this study.

7.4 Recommendations for Future Works

The following analyses were found limited in this study; hence, recommended for future works:

- Integration of hydrologic and hydraulic components, historical flood events, and climate change factors in the analysis on a catchment scale;
- Inclusion of other critical infrastructures in the analysis such as information and communications technology (ICT), financial, food supply, and other networked infrastructures;
- Collection of MDP variables from primary sources; and
- Consideration of ecological/non-structural approaches in disaster risk reduction and climate adaptation strategies in the analysis.

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APPENDICES

Chapter 3

Appendix 1 Selected indicating variables processed with fuzzy logic and corresponding FMVs

Risk Component	Indicating Variable	Fuzzy Membership Operation	Vulnerability (and Risk) Classification s(u: α, β, γ) Low ($u \le \alpha$)	Moderate ($\alpha \le u \le \beta$)	High ($\beta \le u \le \gamma$)	Very High ($u \ge \gamma$)
Hazard	Flood Hazard	Small	See Table 3.4			
Physical Vulnerability	Estimated Period of Settlement	Large	51-105 *0.15-0.77*	105-128 *0.77-0.85*	128-138 *0.85-0.86*	138-161 *0.86-0.94*
Social Vulnerability	Population by Age	Large	8.70-13.73 *0.01-0.23*	13.73-15.34 *0.23-0.38*	15.34-20.38 *0.38-0.60*	20.38-36 *0.60-0.92*
	Total Counts of Registered Businesses	Small	10771-4394 *0.03-0.92*	4394-1800 *0.92-0.99*	1800-745 *0.99-0.994*	745-316 *0.994-1.00*
	Education	Small	74-71 *0.36-0.42*	71-70 *0.42-0.43*	70-66 *0.43-0.49*	66-58 *0.49-0.65*
	IEO	Small	1227-1175 *0.03-0.47*	1175-1160 *0.47-0.73*	1160-1143 *0.73-0.88*	1143-1092 *0.88-0.97*
	IER	Small	1144-1026 *0.03-0.47*	1026-953 *0.47-0.73*	953-908 *0.73-0.88*	9088-80 *0.88-0.97*
	IRSAD	Small	1158-1115 *0.03-0.47*	1115-1089 *0.47-0.73*	1089-1047 *0.73-0.88*	1047-978 *0.88-0.97*
	IRSD	Small	1129-1094 *0.03-0.47*	1094-1082 *0.47-0.73*	1082-1048 *0.73-0.88*	1048-945 *0.88-0.97*
	Insurance (Home & Content in $'000)	Large	415-485 *0.49-0.52*	485-543 *0.52-0.65*	543-591 *0.65-0.76*	591-632 *0.76-0.84*
	Persons in Need of Assistance	Large	0.90-1.67 *0.01-0.20*	1.67-2.22 *0.20-0.29*	2.22-2.99 *0.29-0.49*	2.99-4.10 *0.49-0.92*
	Without Vehicles	Large	3.5-13 *0.00-0.23*	13-17 *0.23-0.54*	17-22 *0.54-0.76*	22-31 *0.76-0.95*
	Residential Tenure - Renting	Large	12-40 *0.01-0.68*	40-53 *0.68-0.80*	53-58 *0.80-0.82*	58-70 *0.82-0.94*
	Total Building	Small	341-54	54-31	31-29	29-6

Risk Component	Indicating Variable	Fuzzy Membership Operation	Vulnerability (and Risk) Classification s(u: α, β, γ)			
			Low ($u \le \alpha$)	**Moderate** ($\alpha \le u \le \beta$)	**High** ($\beta \le u \le \gamma$)	**Very High** ($u \ge \gamma$)
	Value ($'000)		*0.03-0.08*	*0.08-0.94*	*0.94-0.99*	*0.99-1.00*
	Unemployment Rate	Large	1.70-3.39 *0.00-0.04*	3.39-5.53 *0.04-0.18*	5.53-8.26 *0.18-0.77*	8.26-10.40 *0.77-0.91*
	Volunteers	Small	29-26.68 *0.20-0.34*	26.68-23.68 *0.34-0.40*	23.68-19.86 *0.40-0.54*	19.86-15 *0.54-0.87*
	Weekly Personal Income	Large	18.30-25.63 *0.04-0.19*	25.63-29.20 *0.19-0.24*	29.20-36.54 *0.24-0.39*	36.54-51.60 *0.39-0.88*
Exposure	Flooded Residential and Commercial Properties	Large	0-88 *0.17-0.24*	88-1646 *0.24-0.92*	1646-3205 *0.92-0.99*	3205-3293 *0.99-1.00*
	Estimated Resident Population	Large	1347-5781 *0.01-0.51*	5781-8525 *0.51-0.77*	8525-11270 *0.77-0.91*	11270-15704 *0.91-0.98*
	Population Growth Rate	Large	0-1.32 *0.21-0.86*	1.32-2.49 *0.86-0.98*	2.49-3.81 *0.98-0.99*	3.81-5.30 *0.99-1.00*

Note: Upper values are the original attribute values and lower italicised values are the fuzzy membership values

Chapter 3

Appendix 2 Calculated global Moran's I statistics of flood risk and adaptation capacity indicating variables

Hazard Indicating Variables

Distance (m)	HAZARD INDICATING VARIABLES							
	Biological		Building Damage		Chemical		Electricity	
	I	*Zi*	*I*	*Zi*	*I*	*Zi*	*I*	*Zi*
100	-	-	-	-	-	-	0.71	59.05
200	-	-	0.24	139.99	-	-	0.67	79.62
300	-	-	0.20	143.04	-	-	0.65	97.26
400	-	-	0.13	114.95	-	-	0.61	110.06
500	-	-	0.10	98.79	-	-	0.48	105.68
600	-	-	0.06	79.44	-	-	0.39	100.78
700	-	-	0.04	55.28	0.68	21.51	0.33	97.36
800	-	-	0.03	44.94	0.68	24.03	0.26	87.80
900	-	-	0.03	49.14	0.69	26.10	0.22	80.55
1000	-	-	0.03	55.16	0.69	27.28	0.18	73.83
1100	-	-	0.02	49.84	0.69	29.16	0.15	65.70
1200	-	-	0.02	44.40	0.68	28.93	0.12	59.97
1300	-	-	0.01	23.46	0.65	28.20	0.11	55.44
1400	-	-	0.00	4.48	0.62	27.88	0.09	50.05
1500	0.24	18.97	0.00	-5.16	0.54	25.69	0.08	45.12
1600	0.22	18.24			0.48	24.24	0.06	40.00
1700	0.22	19.08			0.41	23.84	0.05	35.94
1800	0.20	19.53			0.35	23.34	0.04	32.47
1900	0.20	21.21			0.33	23.70	0.03	25.30
2000	0.20	22.38			0.29	22.83	0.02	18.79
2100	0.18	21.60			0.27	22.81	0.02	18.09
2200	0.14	19.68			0.24	22.15	0.02	15.95
2300	0.10	16.88			0.23	21.97	0.02	17.44
2400	0.07	13.12			0.19	20.50	0.01	15.80
2500	0.04	9.84			0.13	18.22	0.01	11.56
2600	0.03	8.06			0.11	16.99	0.00	5.10
2700	0.01	5.16			0.06	14.52	0.00	-2.70
2800	-0.01	-0.72			0.02	11.39		
E(I)	-0.0092		-0.00026		-0.0154		-0.0012	

Physical Vulnerability Indicating Variables

Distance (m)	PHYSICAL VULNERABILITY INDICATING VARIABLES									
	Building FSI		Electricity Network		Sewerage Network		Stormwater Network		Water Supply Network	
	I	*Zi*	*I*	*Zi*	*I*	*Zi*	*I*	*Zi*	*I*	*Zi*
100	-	-	-	-	-	-	-	-	-	-
200	0.08	86.78	-	-	-	-	-	-	-	-
300	0.05	69.66	-	-	-	-	0.04	44.53	0.11	142.38
400	0.03	60.91		15.64	-	-	0.03	49.16	0.10	172.77
500	0.02	55.31		17.15	-	-	0.03	48.30	0.09	197.32
600	0.02	52.13		18.04	-	-	0.02	46.09	0.08	212.99
700	0.02	59.64		19.88	-	-	0.02	43.54	0.08	224.38
800	0.02	66.35		21.79	-	-	0.01	39.64	0.07	232.32
900	0.01	60.75		21.35	0.04	30.57	0.01	35.28	0.07	238.26
1000	0.01	56.00		21.71	0.04	28.77	0.01	30.67	0.06	240.80
1100	0.01	57.64		21.29	0.03	27.89	0.01	25.31	0.06	240.05
1200	0.01	63.75		22.79	0.03	26.47	0.01	21.88	0.05	235.76
1300	0.01	66.87		23.12	0.03	25.14	0.00	14.84	0.04	230.36
1400	0.01	65.34		24.77	0.02	23.33	0.00	10.03	0.04	225.32
1500	0.01	66.00		25.38	0.02	23.18	0.00	5.39	0.04	216.77
1600	0.01	64.02		26.09	0.02	22.45	0.00	0.85	0.03	209.28
1700	0.01	63.04		25.08	0.02	21.08			0.03	201.93
1800	0.01	67.39		23.72	0.01	19.44			0.03	195.88
1900	0.01	69.00		23.37	0.01	18.26			0.02	188.69
2000	0.01	69.34		22.38	0.01	18.57			0.02	180.34
2100	0.01	72.74		21.1	0.01	18.15			0.02	172.21
2200	0.01	76.08		19.41	0.01	16.77			0.02	163.41
2300	0.01	76.96		17.04	0.01	16.49			0.02	154.94
2400	0.01	77.97		14.04	0.01	15.86			0.01	147.22
2500	0.01	78.68		11.41	0.01	14.85			0.01	139.86
2600	0.01	79.24		9.73	0.01	14.24			0.01	132.70
2700				9.18					0.01	124.98
2800				6.93					0.01	117.01
2900				4.24					0.01	109.92
3000				2.91					0.01	104.18
3100				1.47						
3200				0.57						
3300				-0.29						
E(I)	-0.000059		-0.00034		-0.0003		-0.00008		-0.00007	

Social Vulnerability Indicating Variables

Distance (m)	SOCIAL VULNERABILITY INDICATING VARIABLES			
	Access to Emergency Services		Emergency Response	
	I	*Zi*	*I*	*Zi*
2600	0.31	14.02	0.31	14.35
2700	0.31	14.58	0.31	14.92
2800	0.29	14.61	0.29	14.96
2900	0.30	15.83	0.30	16.92
3000	0.30	16.26	0.30	16.58
3100	0.28	16.02	0.28	16.29
3200	0.27	16.20	0.26	16.41
3300	0.24	15.40	0.24	15.56
3400	0.23	15.09	0.22	15.20
3500	0.22	15.02	0.21	15.13
3600	0.19	14.09	0.19	14.21
3700	0.18	13.26	0.17	13.37
3800	0.16	12.64	0.16	12.70
3900	0.15	12.12	0.14	12.21
4000	0.13	11.63	0.13	11.70
4100	0.12	10.78	0.11	10.86
4200	0.10	9.60	0.09	9.47
4300	0.08	8.80	0.08	8.60
4400	0.07	8.16	0.07	8.00
4500	0.06	7.23	0.06	7.25
4600	0.04	5.70	0.04	5.72
4700	0.03	4.55	0.02	4.56
4800	0.01	2.94	0.01	2.88
4900	0.01	2.72	0.01	2.75
5000	0.00	2.04	0.00	2.03
5100	-0.01	0.44	-0.02	0.42
5200	-0.02	-0.22	-0.02	-0.19
E(I)	-0.0189		-0.0185	

Exposure Indicating Variables

Distance (m)	EXPOSURE INDICATING VARIABLES									
	Electricity Services		Heritage Sites		Sewerage Services		Stormwater Services		Water Supply Services	
	I	*Zi*	*I*	*Zi*	*I*	*Zi*	*I*	*Zi*	*I*	*Zi*
100	0.35	32.24			0.28	19.68	0.38	57.97	-	-
200	0.27	56.34			0.23	27.94	0.29	81.36	-	-
300	0.23	69.17			0.19	34.49	0.23	101.65	0.73	48.12
400	0.19	79.80			0.16	38.02	0.20	113.62	62.00	64.45
500	0.16	83.42			0.14	41.94	0.18	122.64	0.54	74.40
600	0.14	85.16	0.61	10.02	0.12	44.96	0.15	129.66	0.50	77.03
700	0.12	85.26	0.53	12.22	0.11	47.44	0.14	132.45	0.42	80.40
800	0.10	83.24	0.53	12.22	0.10	48.43	0.12	130.98	0.38	80.95
900	0.13	95.98	0.53	12.22	0.09	49.22	0.10	126.06	0.34	81.23
1000	0.07	73.32	0.43	12.42	0.08	49.22	0.08	120.54	0.30	81.21
1100	0.06	65.92	0.35	12.90	0.07	48.41	0.07	114.23	0.27	80.22
1200	0.05	59.68	0.35	12.90	0.06	47.62	0.06	106.14	0.25	79.43
1300	0.04	53.00	0.31	12.80	0.06	46.03	0.05	99.49	0.22	78.06
1400	0.03	47.20	0.29	13.00	0.05	44.42	0.05	94.68	0.20	77.04
1500	0.02	42.50	0.25	12.97	0.04	42.03	0.04	92.52	0.18	75.82
1600	0.02	37.75	0.25	12.97	0.04	39.81	0.04	91.68	0.16	74.18
1700	0.02	33.49	0.22	12.96	0.03	37.41	0.04	90.88	0.15	72.45
1800	0.02	30.94	0.22	12.96	0.03	35.29	0.03	91.37	0.14	71.36
1900	0.01	29.08	0.19	13.14	0.02	32.80	0.03	93.88	0.13	69.87
2000	0.01	28.47	0.18	13.23	0.02	31.22	0.03	96.92	0.11	68.14
2100	0.01	28.59	0.17	13.13	0.02	29.44	0.03	100.28	0.11	67.12
2200	0.01	30.23	0.17	13.13	0.02	27.77	0.03	104.76	0.10	65.36
2300	0.01	31.67	0.15	12.89	0.02	26.67	0.03	108.77	0.09	64.17
2400	0.01	34.61	0.13	12.77	0.01	25.21	0.03	114.10	0.08	62.90
2500	0.01	38.32	0.12	12.76	0.01	23.86	0.03	117.38	0.07	61.26
2600	0.01	44.01	0.12	12.75	0.01	23.18	0.03	121.11		
2700	0.01	49.93	0.11	12.74	0.01	22.67	0.02	122.10		
2800	0.01	54.91	0.10	12.38	0.01	22.16	0.02	123.25		
2900	0.01	60.38	0.10	12.38	0.01	22.04	0.02	122.12		
3000	0.01	65.32	0.09	12.24	0.01	22.69	0.02	119.60		
3100	0.01	68.94	0.08	12.30						
3200	0.01	70.76	0.08	12.30						
3300	0.01	71.36	0.07	11.92						
3400	0.01	71.44	0.06	11.72						
3500	0.01	70.06	0.06	11.53						
E(I)	-0.00023		-0.0083		-.00004		-0.0002		-0.00092	

Chapter 6

Appendix 3 The summary of different MDP scenarios tested in the study

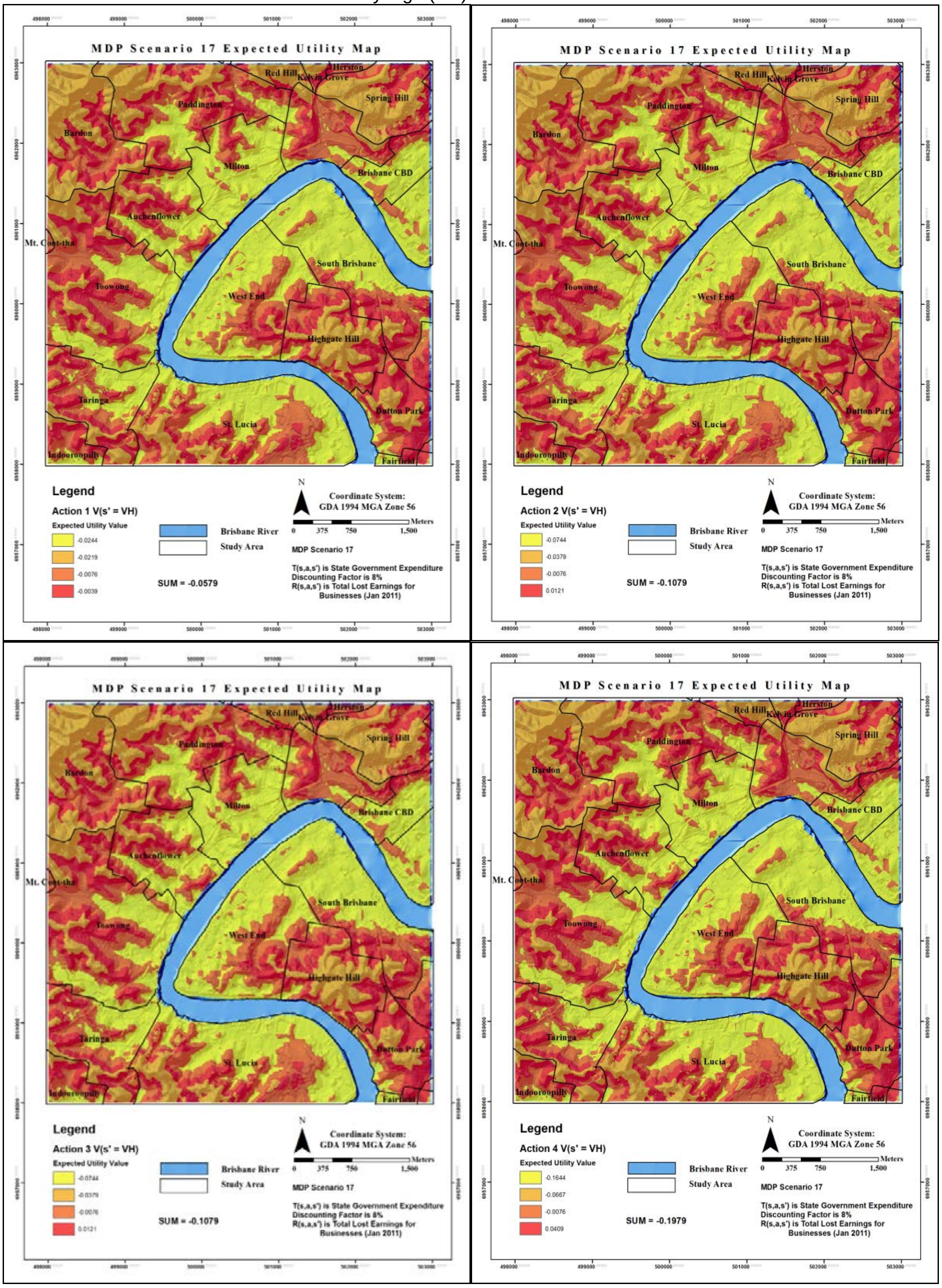
Scenario	Transition Probability *T(s,a,s')*	Discount Factor (*γ*)	Reward *R(s,a,s')*	Survey Date
1	Commonwealth government expenditure	3%	Total lost earnings for businesses	January 2011
2	Commonwealth government expenditure	3%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
3	Commonwealth government expenditure	3%	Total lost earnings for businesses	August 2011
4	Commonwealth government expenditure	3%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
5	Commonwealth government expenditure	8%	Total lost earnings for businesses	January 2011
6	Commonwealth government expenditure	8%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
7	Commonwealth government expenditure	8%	Total lost earnings for businesses	August 2011
8	Commonwealth government expenditure	8%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
9	Commonwealth government expenditure	10%	Total lost earnings for businesses	January 2011
10	Commonwealth government expenditure	10%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
11	Commonwealth government expenditure	10%	Total lost earnings for businesses	August 2011
12	Commonwealth government expenditure	10%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
13	State government expenditure	3%	Total lost earnings for businesses	January 2011

Scenario	Transition Probability *T(s,a,s')*	Discount Factor (*γ*)	Reward	
			R(s,a,s')	Survey Date
14	State government expenditure	3%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
15	State government expenditure	3%	Total lost earnings for businesses	August 2011
16	State government expenditure	3%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
17	State government expenditure	8%	Total lost earnings for businesses	January 2011
18	State government expenditure	8%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
19	State government expenditure	8%	Total lost earnings for businesses	August 2011
20	State government expenditure	8%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
21	State government expenditure	10%	Total lost earnings for businesses	January 2011
22	State government expenditure	10%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
23	State government expenditure	10%	Total lost earnings for businesses	August 2011
24	State government expenditure	10%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
25	Combined government expenditure	3%	Total lost earnings for businesses	January 2011
26	Combined government expenditure	3%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
27	Combined government expenditure	3%	Total lost earnings for businesses	August 2011
28	Combined government	3%	Total lost earnings as a percentage of	August 2011

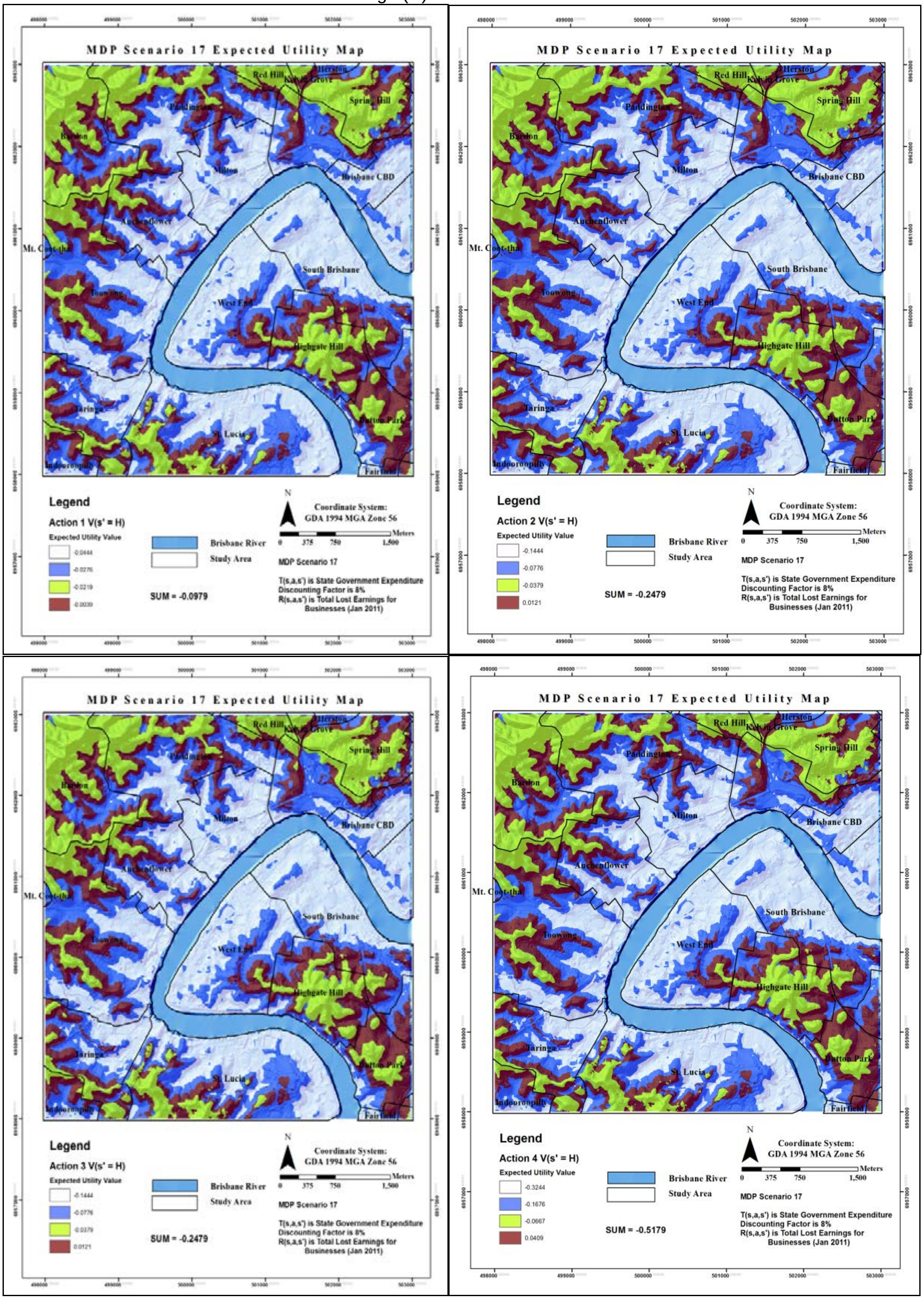
Scenario	**Transition Probability *T(s,a,s')***	**Discount Factor (*γ*)**	**Reward**	
			R(s,a,s')	**Survey Date**
	expenditure		annual turnover for businesses	
29	Combined government expenditure	8%	Total lost earnings for businesses	January 2011
30	Combined government expenditure	8%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
31	Combined government expenditure	8%	Total lost earnings for businesses	August 2011
32	Combined government expenditure	8%	Total lost earnings as a percentage of annual turnover for businesses	August 2011
33	Combined government expenditure	10%	Total lost earnings for businesses	January 2011
34	Combined government expenditure	10%	Total lost earnings as a percentage of annual turnover for businesses	January 2011
35	Combined government expenditure	10%	Total lost earnings for businesses	August 2011
36	Combined government expenditure	10%	Total lost earnings as a percentage of annual turnover for businesses	August 2011

Appendix 4 The MDP expected utility maps for scenarios 17 and 29

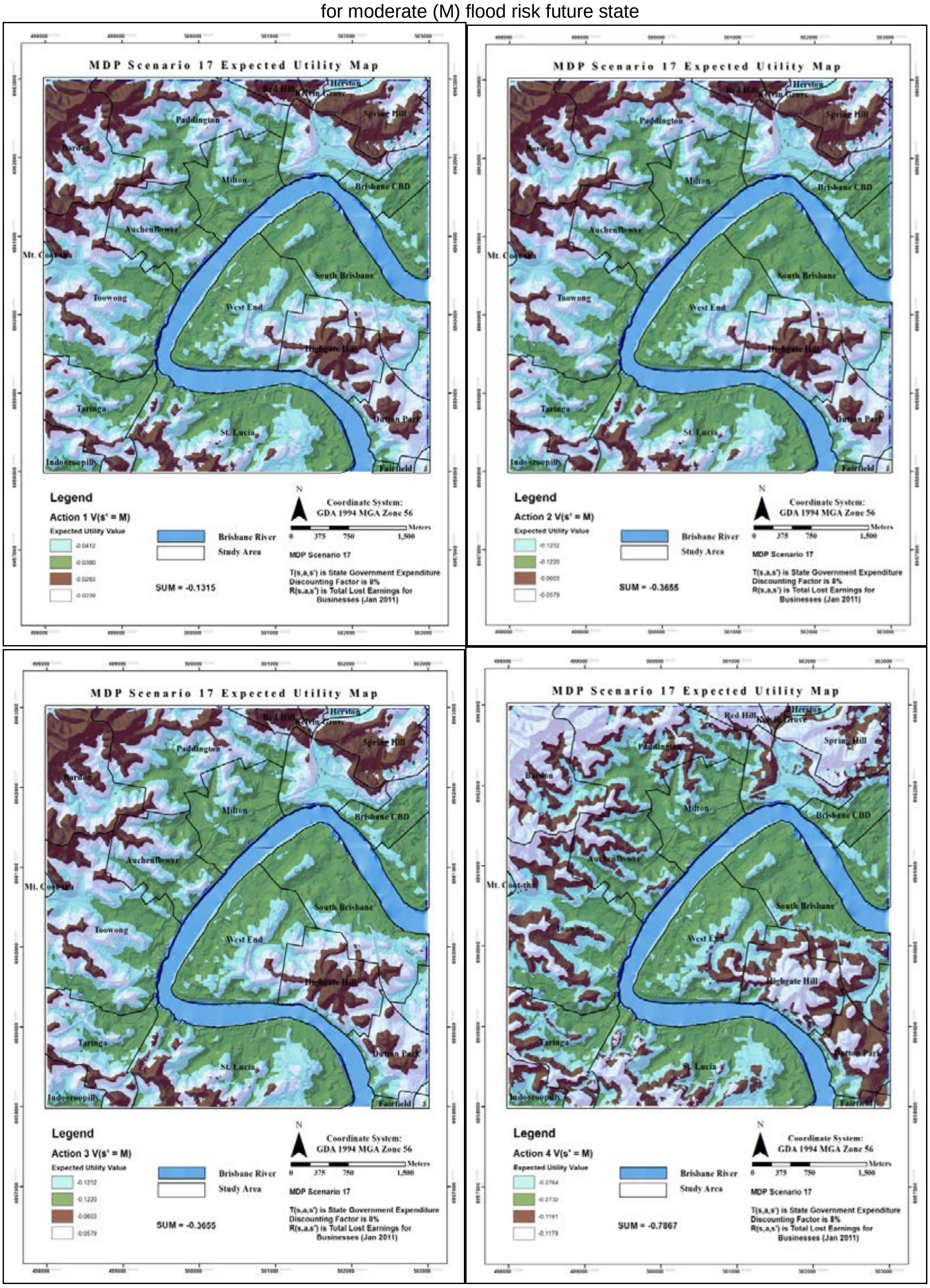
Appendix 4.1 The MDP scenario 17 expected utility maps
for very high (VH) flood risk future state



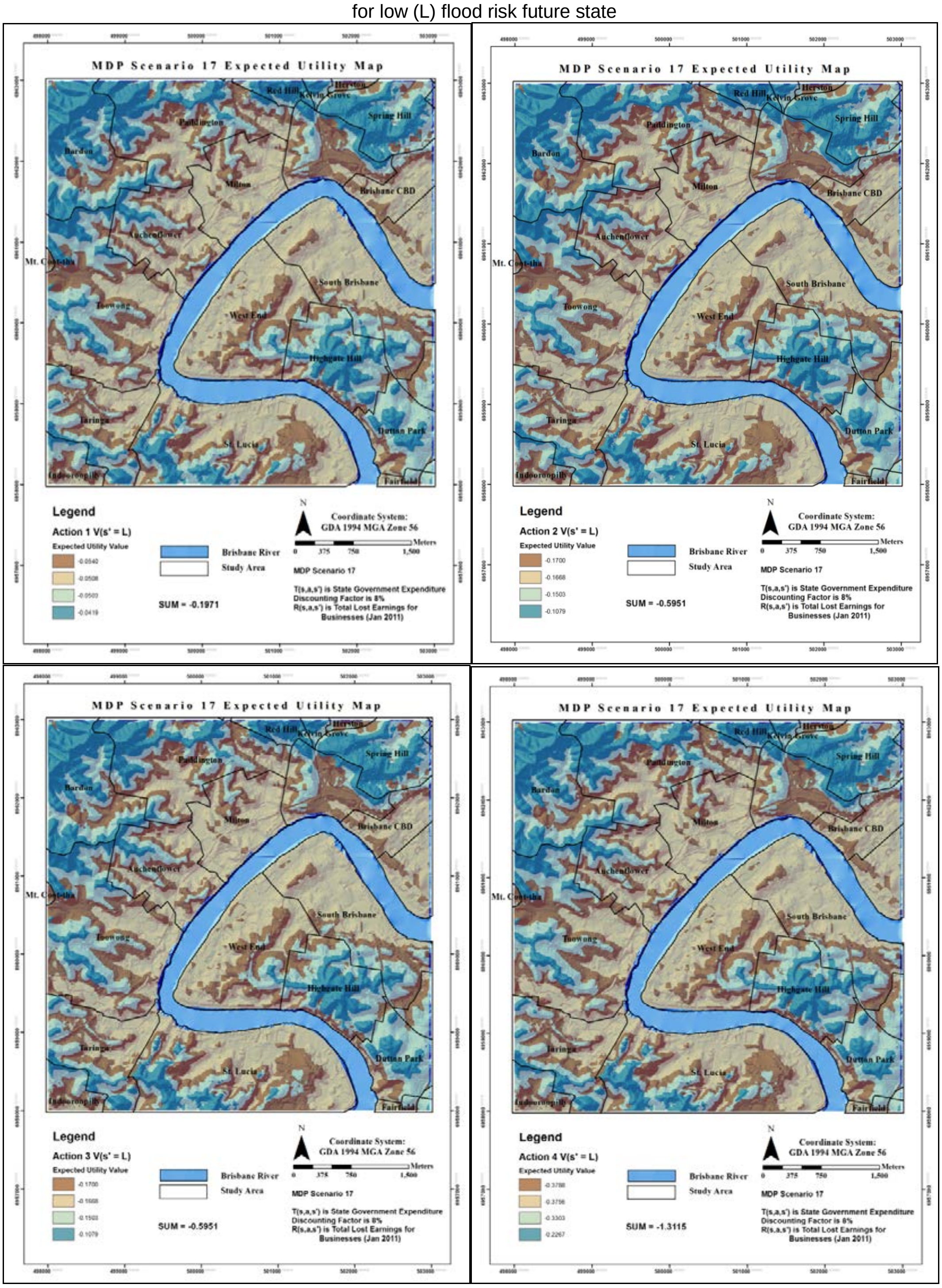
Appendix 4.2 The MDP scenario 17 expected utility maps for high (H) flood risk future state



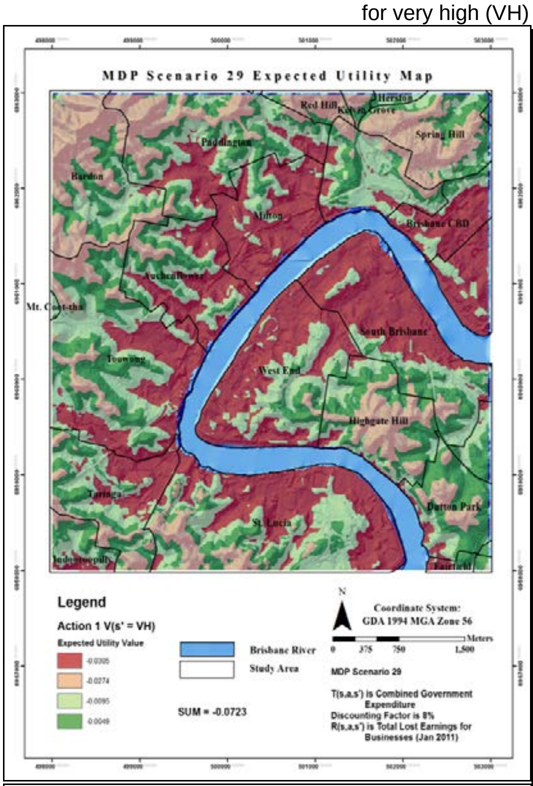
Appendix 4.3 The MDP scenario 17 expected utility maps
for moderate (M) flood risk future state

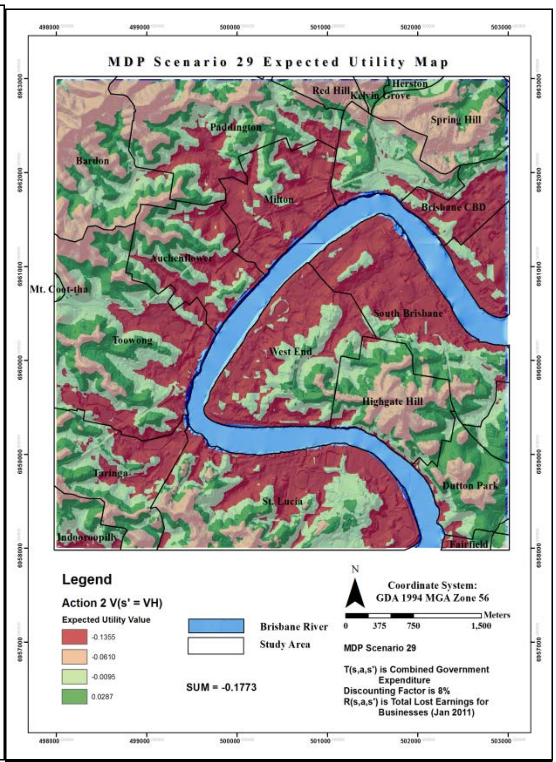


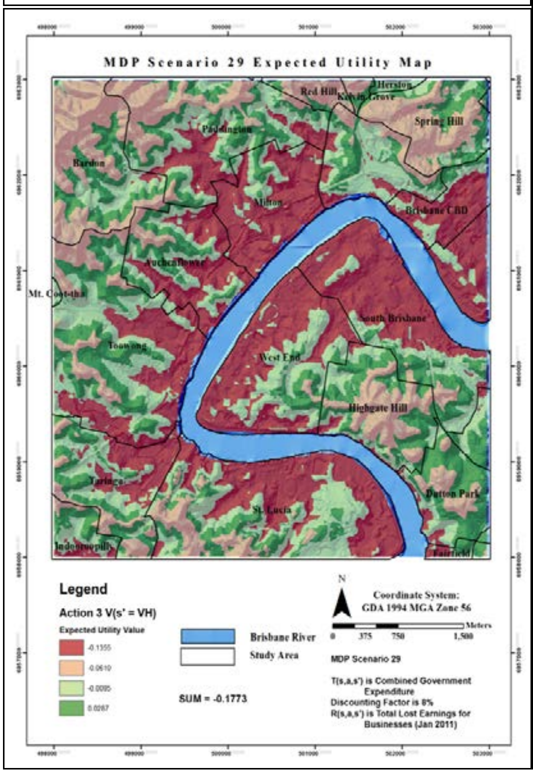
Appendix 4.4 The MDP scenario 17 expected utility maps for low (L) flood risk future state

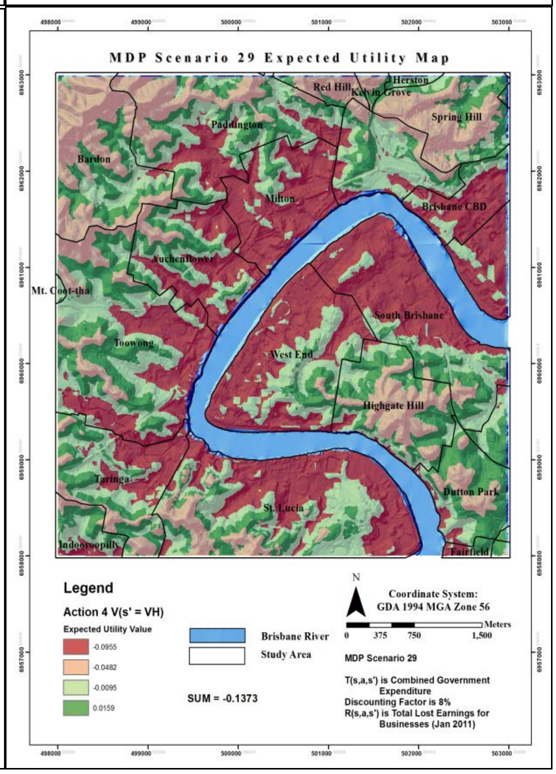


Appendix 4.5 The MDP scenario 29 expected utility maps for very high (VH) flood risk future state

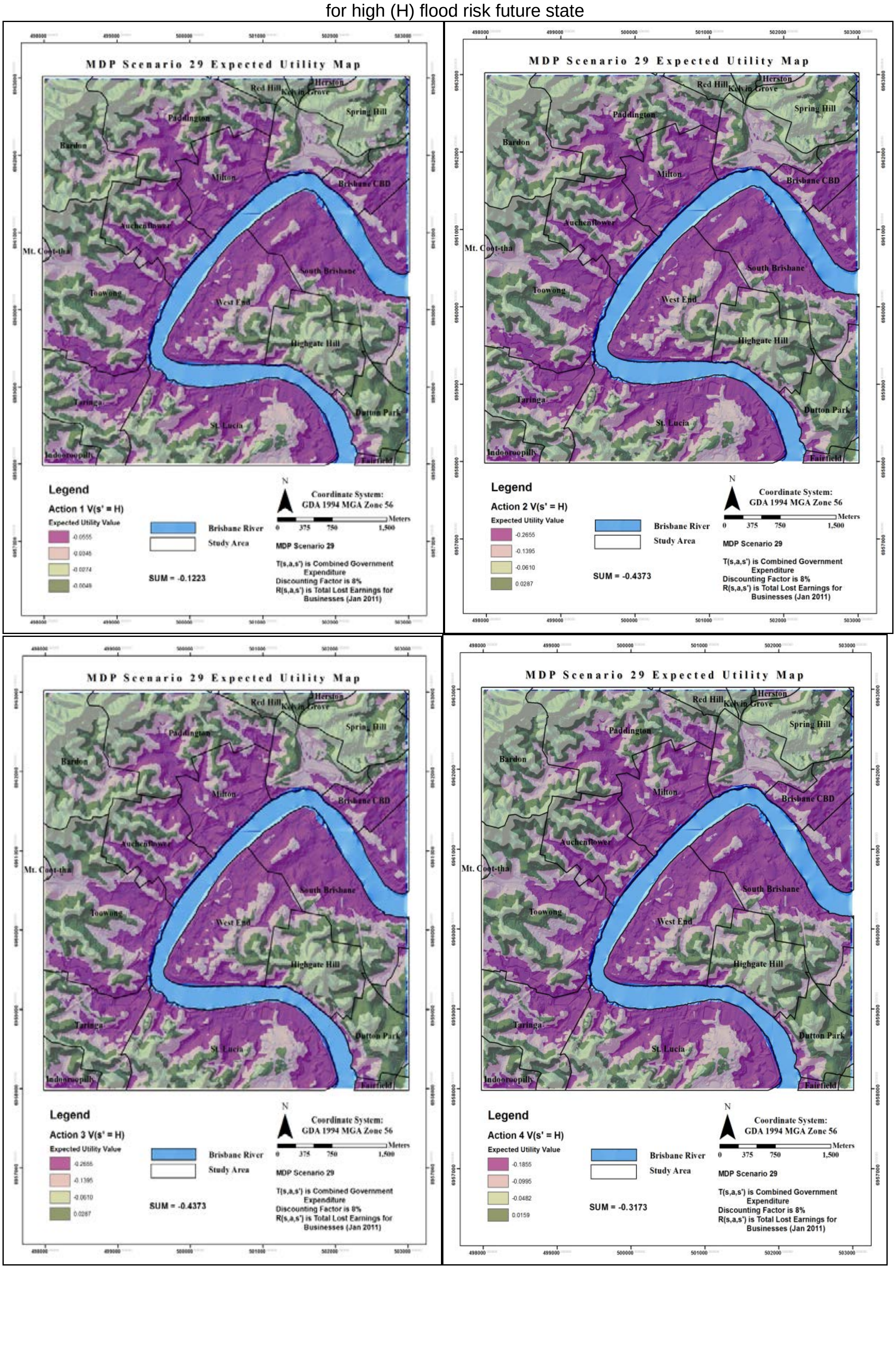




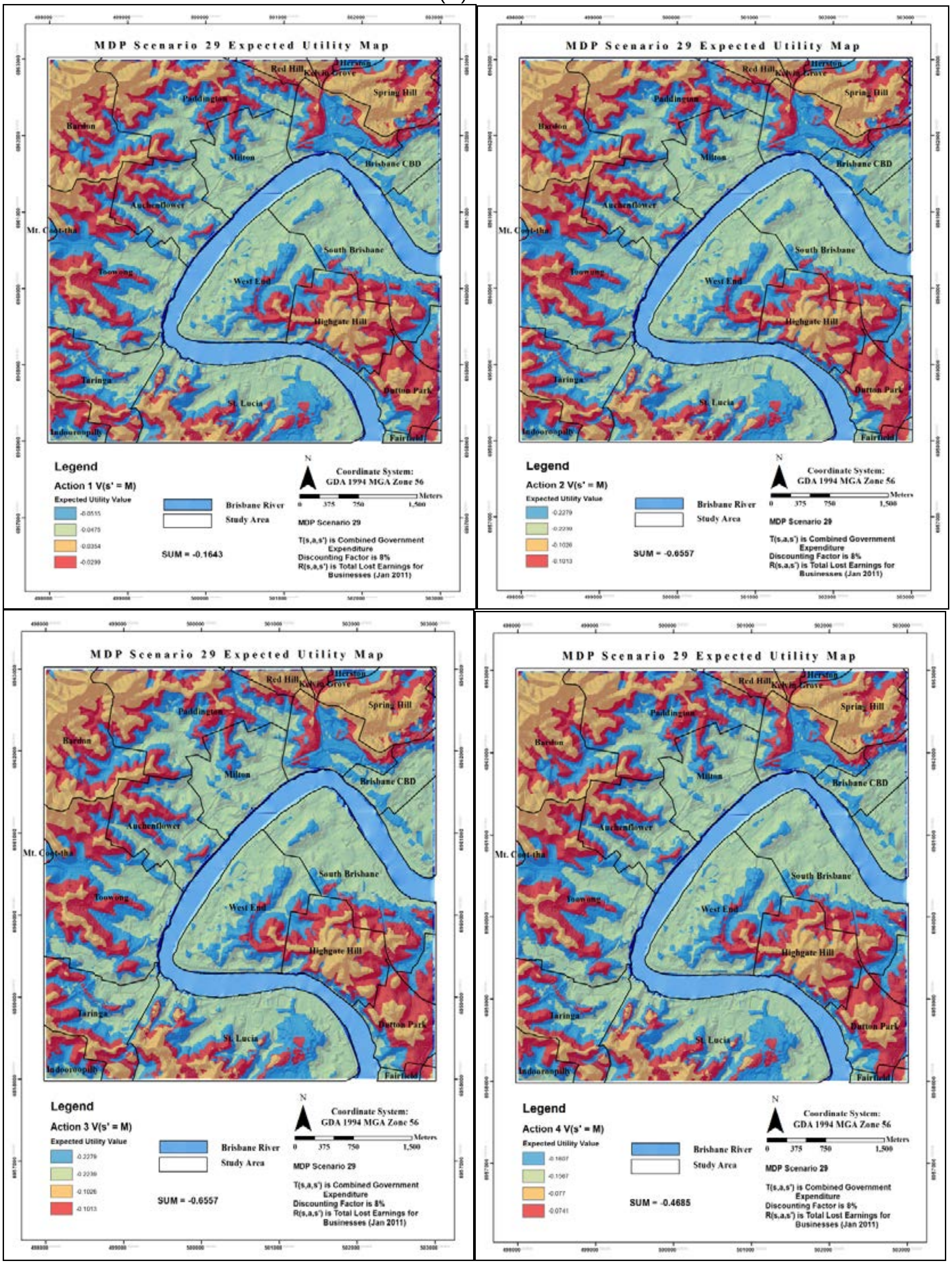




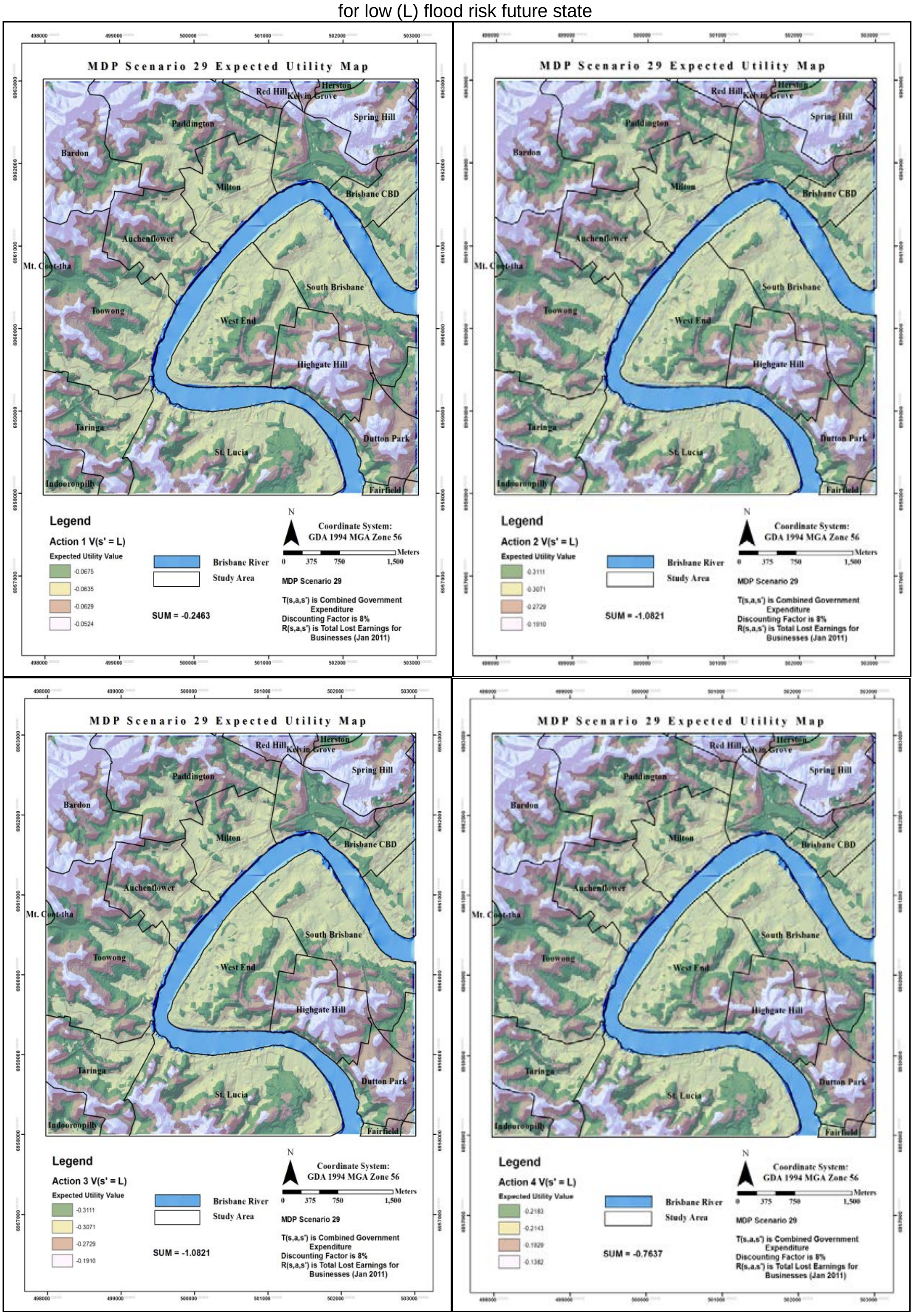
Appendix 4.6 The MDP scenario 29 expected utility maps
for high (H) flood risk future state



Appendix 4.7 The MDP scenario 29 expected utility maps for moderate (M) flood risk future state



Appendix 4.8 The MDP scenario 29 expected utility maps for low (L) flood risk future state



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