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Vulnerability assessment of urban community and critical infrastructures for integrated flood risk management and climate adaptation strategies

Rudolf Espada, Armando Apan, Kevin McDougall,

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Rudolf Espada
School of Agricutlural, Computational and Environmental Sciences, and International Centre for Applied Climate Sciences, University of Southern Queensland, Toowoomba, Australia

Armando Apan
School of Civil Engineering and Surveying, and International Centre for Applied Climate Sciences, University of Southern Queensland, Toowoomba, Australia, and

Kevin McDougall
School of Civil Engineering and Surveying, University of Southern Queensland, Toowoomba, Australia

Abstract

Purpose – The purpose of this paper was to develop an integrated framework for assessing the flood risk and climate adaptation capacity of an urban area and its critical infrastructures to help address flood risk management issues and identify climate adaptation strategies.

Design/methodology/approach – Using the January 2011 flood in the core suburbs of Brisbane City, Queensland, Australia, various spatial analytical tools (i.e. digital elevation modeling and urban morphological characterization with 3D analysis, spatial analysis with fuzzy logic, proximity analysis, line statistics, quadrat analysis, collect events analysis, spatial autocorrelation techniques with global Moran's I and local Moran's I, inverse distance weight method, and hot spot analysis) were implemented to transform and standardize hazard, vulnerability, and exposure indicating variables. The issue on the sufficiency of indicating variables was addressed using the topological cluster analysis of a two-dimension self-organizing neural network (SONN) structured with 100 neurons and trained by 200 epochs. Furthermore, the suitability of flood risk modeling was addressed by aggregating the indicating variables with weighted overlay and modified fuzzy gamma overlay operations using the Bayesian joint conditional probability weights. Variable weights were assigned to address the limitations of normative (equal weights) and deductive (expert judgment) approaches. Applying geographic information system (GIS) and appropriate equations, the flood risk and climate adaptation capacity indices of the study area were calculated and corresponding maps were generated.

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Findings – The analyses showed that on the average, 36 (approximately 813 ha) and 14 per cent (approximately 316 ha) of the study area were exposed to very high flood risk and low adaptation capacity, respectively. In total, 93 per cent of the study area revealed negative adaptation capacity metrics (i.e. minimum of −23 to <0), which implies that the socio-economic resources in the area are not enough to increase climate resilience of the urban community (i.e. Brisbane City) and its critical infrastructures.

Research limitations/implications – While the framework in this study was obtained through a robust approach, the following are the research limitations and recommended for further examination: analyzing and incorporating the impacts of economic growth; population growth; technological advancement; climate and environmental disturbances; and climate change; and applying the framework in assessing the risks to natural environments such as in agricultural areas, forest protection and production areas, biodiversity conservation areas, natural heritage sites, watersheds or river basins, parks and recreation areas, coastal regions, etc.

Practical implications – This study provides a tool for high level analyses and identifies adaptation strategies to enable urban communities and critical infrastructure industries to better prepare and mitigate future flood events. The disaster risk reduction measures and climate adaptation strategies to increase urban community and critical infrastructure resilience were identified in this study. These include 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 implications of integrating disaster risk reduction and climate adaptation strategies were further examined.

Originality/value – The newly developed spatially explicit analytical technique, identified in this study as the Flood Risk-Adaptation Capacity Index-Adaptation Strategies (FRACIAS) Linkage/Integrated Model, allows the integration of flood risk and climate adaptation assessments which had been treated separately in the past. By applying the FRACIAS linkage/integrated model in the context of flood risk and climate adaptation capacity assessments, the authors established a framework for enhancing measures and adaptation strategies to increase urban community and critical infrastructure resilience to flood risk and climate-related events.

Keywords Risk analysis, Infrastructure, Vulnerability, Flooding, Built environment, Capacity

Paper type Research paper

1. Introduction

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 (Bureau of Transport and Regional Economics (BTRE), 2002; 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, and then extrapolating to future probabilities (Baer, 2008). This flood mapping technique produces a better understanding of the causes and magnitude of disastrous flooding and provides flood information necessary to support development of an integrated strategy to improve disaster resilience and preparedness in the flood hazard areas (Teasdale *et al.*, 2009).

With the widespread use of geographic information system (GIS) and database resources, models and inundation maps can be easily updated and improved, detailed flood information can be generated and potential hazards or risks can be determined (Teasdale *et al.*, 2009). While GIS can offer technological advances in climate science and disaster management, this tool has a limited base in the integrated modeling of flood risk and climate adaptation (CA) capacity for vulnerability assessment of urban community and its critical infrastructures. Patwardhan *et al.* (2009) emphasized that the big challenge in GIS is the integration of new knowledge with new approaches for knowledge generation. Engineering profession involved in critical infrastructure management should likewise respond to this challenge by working new ways using the integrated systems approach (Collins *et al.*, 2011). Hence, this study aimed to generate a novel GIS-based approach of assessing vulnerability of urban community and critical infrastructures for integrated flood risk management and CA strategies. Specifically, the objective of this study was to use spatial modeling to develop flood risk and CA capacity indices/metrics that will aid to identify CA strategies and address flood risk management issues of an urban area and its critical infrastructures.

2. Review of literature

2.1 South east Queensland floods

Australia has historically been impacted by various flood disasters with the recent one happened in January 2011. The average direct annual cost of flooding between 1967 and 1999 has been estimated at US$314m. The most costly flood was recorded in 1974 amounting to US$2.9bn (Geoscience Australia, 2010b), which has been, however, superseded by the 2010/2011 Queensland floods.

Since the disastrous 1893 floods, Brisbane has subsequently been flooded in January 1974 due to Cyclone Wanda, which washed away many houses, and unfortunately killed 14 people [Australian Bureau of Statistics (ABS), 2008]. In December of the same year, Cyclone Tracy brought devastating floods to Darwin with buildings were totally destroyed or badly damaged, 65 people died, and the remaining population was evacuated [Australian Bureau of Statistics (ABS), 2008]. Building codes and disaster planning since then have been given much attention [Australian Bureau of Statistics (ABS), 2008].

From December 2010 to January 2011, a series of floods again hit the country, particularly in the state of Queensland, with three quarters of the state declared a disaster zone and over 2.5 million people were affected [State of Queensland (SoQ), 2010]. Thirty-five people died, 29,000 homes and businesses suffered from inundation, and the amount of damages from flood alone has been in excess of US$5bn (Queensland Floods Commission of Inquiry, 2011).

2.2 Flood risk assessment

The Earth is exposed to various environmental risks, natural disasters and hazards. Westen (2000) emphasized that a potentially damaging phenomenon (hazard), such as flood is not considered a disaster when it occurs in uninhabited areas. Accordingly, it is called disaster when it occurs in populated area, and brings damage, loss or destruction to the socio-economic system.

UNISDR (2009) defined *risk assessment* as a methodology to determine 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. Mathematically, risk can be expressed in the following forms (Mirfenderesk and Corkill, 2009; Downing, 2002; Hughey and Bell, 2010):

$$Risk = Hazard \times Vulnerablity \times Exposure \quad (1)$$

$$Risk = Hazard + Vulnerability \quad (2)$$

$$Risk = Hazard + Vulnerability - Adaptation\ \ Capacity \quad (3)$$

2.3 Adaptation capacity

UNISDR (2009) defined *capacity* as the combination of all the strengths, attributes and resources available within a community, society or organization that can be used to achieve agreed goals. This is a collective definition of the term capacity as differentiated from coping capacity which encompasses individual, people, and community or organizational capacity. In contrast, capacity includes infrastructure and internal processes or external forces, whilst coping capacity requires continuing awareness, resources, and good management during crises or adverse conditions that would contribute to the reduction of disaster risks (UNISDR, 2009). The term *coping capacity* is defined as the ability of the people, organizations and systems, using available skills and resources, to face and manage adverse conditions, emergencies or disasters (Bell, 2010); hence focusing on social dimensions.

Within the context of climate change, *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. This term refers to changes in processes, practices or structures to moderate or offset potential damages or to take advantages of opportunities associated with changes in climate (IPCC, 2001; Bosello *et al.*, 2009) including anticipatory and reactive, autonomous or spontaneous and planned, and public and private (IPCC, 2001; Gallopin, 2006).

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 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) and, hence, may also be referred to as *response capacity* (Tompkins and Adger, 2005; Preston and Stafford-Smith, 2009).

According to UNISDR and EUR-OPA (2011), adaptation and disaster risk reduction (DRR) are both short-term and long-term processes requiring the former 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. As such, DRR 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). Thus, this study was designed to achieve the objective of developing a framework for the integrated flood risk and CA capacity metrics for vulnerability assessment of critical urban infrastructures.

By mathematical transformation, equation (3) can be expressed as (Espada *et al.*, 2012, 2013a, 2013b):

$$Adaptation\ \ Capacity = Vulnerability - (Risk + Hazard) \tag{4}$$

2.4 Issues on geographic information system-based climate risk assessment

To prepare for natural and man-made disasters and mitigate their impacts, policy makers and community can plan for pre- and post-disaster response efforts (Abukhater, 2011). The use of GIS provides effective planning tools to predict fire hazards, for example, by modeling areas that are highly vulnerable to fire and measure its impacts to community's assets and resources including the associated costs and fatalities (Abukhater, 2011). In China, a case study was conducted to assess and manage the flood disaster risk under future climate change and developed the spatial pattern of flood disaster risk grades showing regions of highest risk (Shao-Hong *et al.*, 2012). In the same country, particularly in Huaihe River basin, the response of flood risk caused by climate change and social development was assessed based on GIS and natural disaster risk assessment theory and determined the high risk areas in different periods and spaces; hence, the results provide useful information for making disaster mitigating plans (Wu *et al.*, 2017).

Despite environmental risk assessment using GIS has made steady progress over the past decade, methodological problems still exist which can be generally categorized into:

- limitation of actual data and measurement used;
- the scale and/or resolution of the analysis; and
- the type of statistical or spatial analysis applied (McMaster *et al.*, 1997).

In using the spatial and temporal standardization method to standardized flood risk index, for example, the one weight calibration method offers one-sidedness results (Wu *et al.*, 2016); hence, Wu *et al.* (2016) used the analytic hierarchy process (AHP) and entropy weight methods to reduce this limitation. To address the issue of large or global scale risk assessment, Torresan *et al.* (2016) applied DESYCO, a GIS-based decision support system, to understand the risks that climate change poses at the regional/subnational scale and presented the capabilities of the tool to support flood risk reduction, shoreline planning, among others. The significance of regional spatial planning and urban design has been further emphasized in the work of Cavan and Kingston (2012); hence, they applied the tool called Green and Blue Space Adaptation for Urban Areas and Eco Towns (GRaBS). However, the tool is limited by the availability of geospatial data and information which can affect the types of outputs the tool can provide (Cavan and Kingston, 2012).

Generally, generating the new methods and tools for natural hazard and climate impact research taking into account climate change, exposure and vulnerability is a major challenge (Valentina *et al.*, 2014). Furthermore, 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). 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-organizing neural network (SONN) to select appropriate indicating variables and aggregate them with joint conditional probable weights based on Bayesian theory for flood risk and CA capacity modeling.

3. Study area

The study area is located in the core suburbs of Brisbane City, the Queensland's capital in Australia. 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 (Middelmann, 2002). Including the Lockyer Creek and Bremer River catchments, around 6,500 km^2 (approximately 50 per cent) of the Brisbane River catchment is below Wivenhoe and Somerset Dams (Robinson, 2011).

Brisbane City had an US$85bn worth of economy in 2011 [Brisbane City Council (BCC), 2012]. However, the City's economic progress together with more than a million estimated residents, had been hampered and devastated recently by 2010/2011 floods. In January 2011, flood waters in Brisbane peaked at 4.46 meters making it one of the worst floods in the city's recorded history with significant damage to transport, infrastructure, and residential properties (Queensland Museum, 2011).

Comprising an area of approximately 2,200 ha, the study area includes the 22 central suburbs of Brisbane City as shown in Figure 1.

4. Research methods

This study is part of a research project which aimed to develop an integrated approach of formulating CA strategies to reduce vulnerability of an urban community and infrastructure assets from floods and the effects of climatic variability. Figure 2 is the input-process-output (IPO) model specifically used in the 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 (Table I).

Under the process component, four main GIS operation challenges were addressed to generate the flood risk and adaptation capacity models. The first challenge was to identify analytical tools with ArcGIS 10 (ESRI, 2011) that will transform indicating variables for flood hazard, vulnerability and exposure into standardized raster formats.

After having the data sets transformed and standardized, this study was further challenged to evaluate which of these variables have certain degree of direct correlation (i.e. 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 analyzed the topological clusters of these indicating variables using the self-

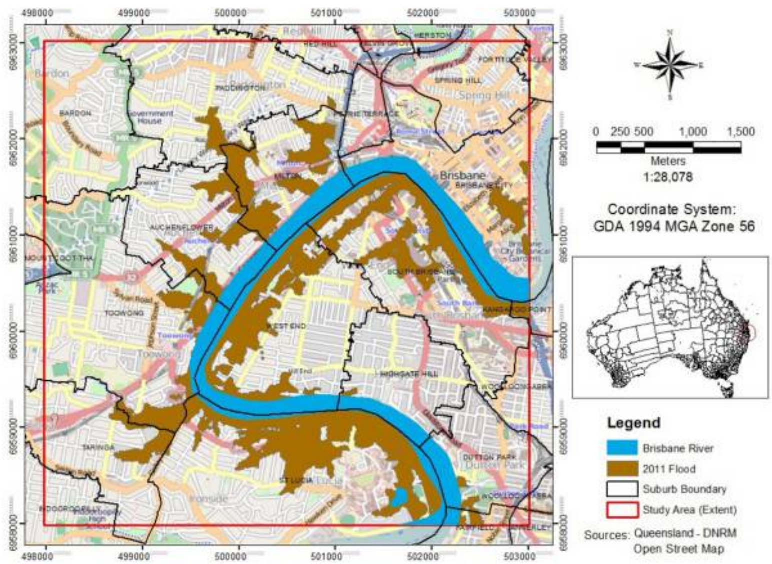


Figure 1.
Location of the study area

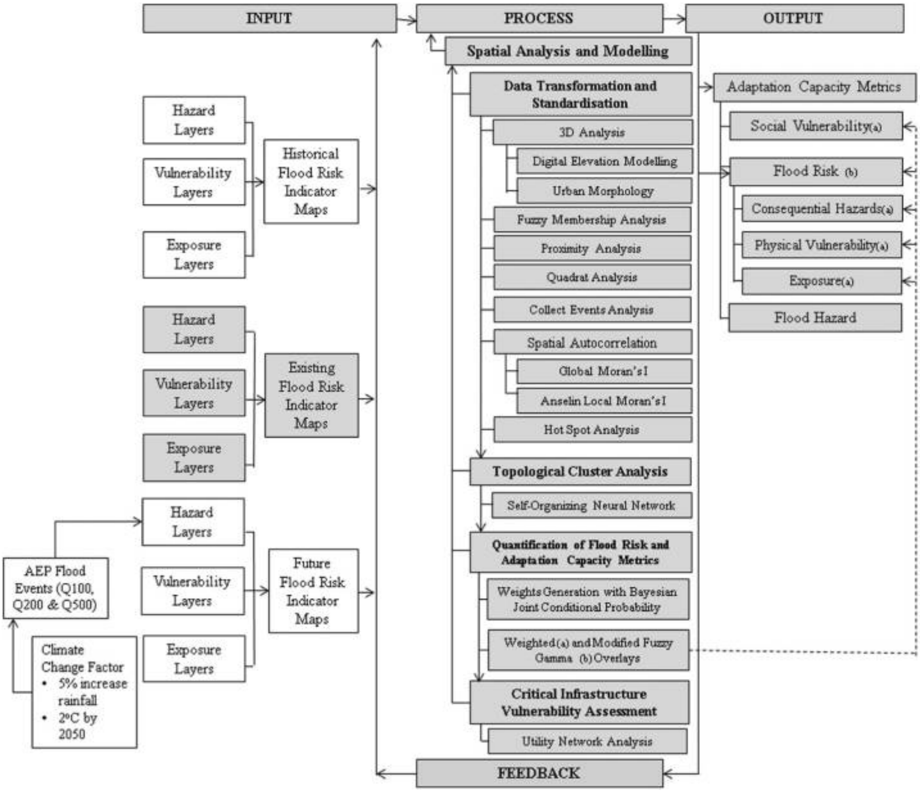


Figure 2.
The input-process-output (IPO) model used in the study

organizing 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 or unequal weights of indicating variables were generated using Bayesian joint conditional probability. These probability values were used in the weighted overlay operations in generating hazard, vulnerability, and exposure indices. These indices were in turn used in calculating the flood risk metrics using the modified fuzzy gamma function in ArcGIS 10. This was done to both consider equations (1) and (2) in a single mathematical operation and avoid confusion as to which equation will be operationalized. Applying equation (4), the CA capacity metrics were also generated.

Finally, the generated outputs (i.e. flood risk and adaptation capacity metrics) were then applied in assessing the vulnerability of urban community, in general, and critical infrastructures, in particular. These infrastructures include building properties, heritage sites, electricity, roads and rails, sewerage, stormwater and water supply.

4.1 Data transformation and standardization

The development of indices for flood risk and CA capacity is a daunting task particularly when it involves datasets that are represented in varying formats. This study used available

Flood risk/CA capacity component	Indicating variable	Joint conditional probable weight Electricity	Roads and rails	Sewerage
Hazard	Biological	0.22	0.22	0.22
	Building Damage	0.22	0.22	0.22
	Chemical	0.24	0.24	0.24
	Electricity	0.22	0.22	0.22
	Flood	0.10	0.10	0.10
Physical vulnerability	Building FSI	0.35	0.37	0.42
	Electricity	0.28	NA	NA
	Period of settlement	0.37	0.38	x
	Roads and rails	NA	0.25	NA
	Sewerage	NA	NA	0.58
	Stormwater	NA	NA	NA
	Water supply	NA	NA	NA
Social vulnerability	Age	0.06	0.06	0.06
	Total count of registered businesses	0.08	0.08	0.07
	Educational qualification	0.05	0.05	0.04
	Access to emergency services	x	x	0.09
	ERT	x	x	0.07
	IEO 2011	0.07	0.07	0.06
	IER 2011	0.06	0.06	0.04
	IRSAD 2011	0.05	0.05	0.04
	IRSD 2011	0.07	0.07	0.06
	Home and content insurance	0.09	0.09	0.06
	Persons in need of assistance	0.06	0.06	0.04
	Vehicle ownership	0.05	0.05	0.04
	Residential tenure (Rental)	0.07	0.07	0.05
	Total building value	0.13	0.13	0.10
	Un-employment	0.05	0.05	0.04
	Volunteer	0.05	0.05	x
	Weekly income	0.06	0.06	0.04
Exposure	Electricity	0.23	NA	NA
	Flooded properties	0.39	0.51	0.38
	Heritage sites	x	x	x
	2011 population	0.20	0.26	0.20
	Population growth rate	0.18	0.23	0.18
	Sewerage	NA	NA	0.24
	Stormwater	NA	NA	NA
	Water supply	NA	NA	NA
	Selected (No.)	27	27	27
	Total (No.)	30	30	30
		Storm Water	Water Supply	Integrated Infra-structures
Hazard	Biological	0.22	0.22	0.22
	Building Damage	0.22	0.22	0.22
	Chemical	0.24	0.24	0.24
	Electricity	0.22	0.22	0.22
	Flood	0.10	0.10	0.10
Physical vulnerability	Building FSI	0.28	0.30	0.13
	Electricity	NA	NA	0.10
	Period of settlement	0.30	0.39	0.14

(*continued*)

Table I. Indicating variables used in the SOM analysis and corresponding Bayesian joint conditional probable weights

Flood risk/CA capacity component	Indicating variable	Joint conditional probable weight Electricity	Roads and rails	Sewerage
	Roads and rails	NA	NA	0.09
	Sewerage	NA	NA	0.18
	Stormwater	0.42	NA	0.19
	Water supply	NA	0.31	0.17
Social vulnerability	Age	0.06	0.07	0.05
	Total count of registered businesses	0.08	0.08	0.07
	Educational qualification	0.05	0.05	0.04
	Access to emergency services	x	x	0.09
	ERT	x	x	0.07
	IEO 2011	0.07	0.07	0.06
	IER 2011	0.06	0.06	0.05
	IRSAD 2011	0.05	0.05	0.05
	IRSD 2011	0.07	0.07	0.06
	Home and content insurance	0.09	0.08	0.07
	Persons in need of assistance	0.06	0.06	0.05
	Vehicle ownership	0.05	0.05	0.04
	Residential tenure (Rental)	0.07	0.07	0.06
	Total building value	0.13	0.13	0.11
	Un-employment	0.05	0.05	0.04
	Volunteer	0.05	0.05	0.04
	Weekly income	0.06	0.06	0.05
Exposure	Electricity	NA	NA	0.12
	Flooded properties	0.40	0.31	0.20
	Heritage sites	x	0.12	0.08
	2011 population	0.21	0.16	0.10
	Population growth rate	0.18	0.14	0.09
	Sewerage	NA	NA	0.13
	Stormwater	0.21	NA	0.10
	Water supply	NA	0.27	0.18
	Selected (No.)	27	28	30
	Total (No.)	30	30	30

Notes: IEO – index of education and occupation; IER – index of economic resources; IRSAD – index of relative socio-economic advantage and disadvantage; IRSD – index of relative socio-economic disadvantage

Table I.

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 standardized food risk and CA capacity indices in a uniform raster format. From Figure 2, we operationalized the following analytical tools:

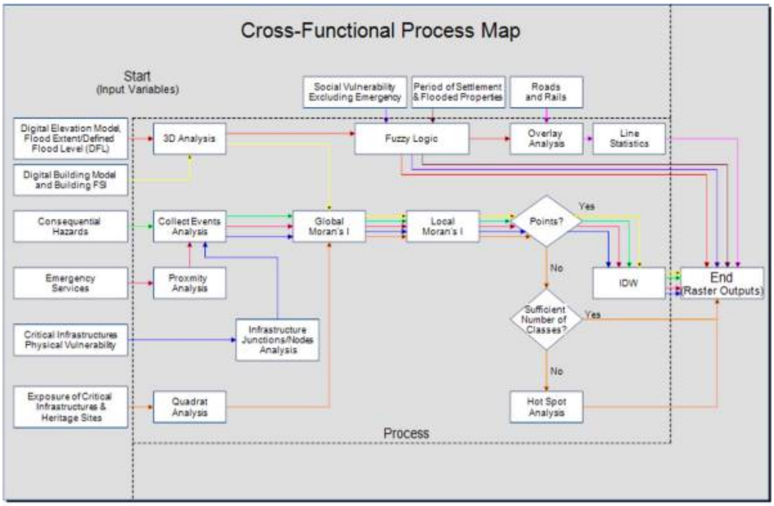
- digital elevation modeling (DEM) and urban morphological characterization with 3D analysis;
- spatial analysis with fuzzy logic;
- proximity analysis;
- line statistical analysis;

- quadrat analysis;
- spatial analysis with collect events analysis;
- spatial autocorrelation; and
- hot spot analysis.

Discussed comprehensively in the following sub-sections, each of this preliminary analytical technique was used according to the type of geographic feature being represented by the indicating variable (Table I). The transformation and standardization techniques were generally guided by a cross-functional process map as shown in Figure 3.

4.1.1 Digital elevation modeling and urban morphological characterization with three-dimensional analysis. 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 as input in flood hazard simulation. Using the ground classification value (i.e. 2), the LiDAR points in LAS format was imported into multipoint ground feature class in ArcGIS 10 platform through the 3D Analyst tool. An interpolation technique known as inverse distance weight (IDW) was then performed using the multipoint ground feature class to represent a continuous terrain surface. To find the areas that had been flooded in January 2011, the flood extent was overlaid with the generated DEM and further processed with fuzzy "small" membership function to reclassify 0 as low flood risk and 1 as very high flood risk.

To characterize the urban morphology specifically the building floor space index (FSI) of the study area, building parameters were extracted from LiDAR point cloud data. Building FSI was calculated by using the buildings' space area and height parameters and mathematically operationalized as the ratio between the building volume and the corresponding Voronoi diagram's cell area (Hamaina *et al.*, 2012). The result was further analyzed with spatial autocorrelation techniques specifically the Global Moran's I and



Note: The color lines represent the paths of data transformation and standardization

Figure 3.
The cross-functional process map used in the study

Anselin Local Moran's I to generate 5 m-gridded map. The output map was reclassified to represent the building's physical vulnerability of the area. 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.

4.1.2 Spatial analysis with fuzzy logic. Introduced by Zadeh (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). Utilizing 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 linear and monotonous operation of indicating variables (Hinkel, 2011). Fuzzification is the process of converting attributes into a homogenous scale by assigning memberships with respect to predefined fuzzy subsets (Sadiq *et al.*, 2004). By way of example, flood risk attributes assigned with high FMVs (i.e. close to 1) may indicate very high flood risk in the generated map.

4.1.3 Proximity analysis. Fifty-four emergency services (i.e. police stations including beat shopfronts, fire and rescue stations, hospitals and medical centers, and January 2011 flood evacuation center) were analyzed using proximity analysis. These points were digitized 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). ERT 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 30 kilometers per hour (kph) 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. The results of proximity analyses were then further analyzed with spatial autocorrelation techniques to cluster the point representations of emergency services. The derived values were then interpolated with 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.

4.1.4 Line statistical analysis. The neighborhood statistic of line features was equally significant in transforming and standardizing the roads and rails networks into a raster map. Using the line statistic tool in ArcGIS 10 with mean as the type of statistic, the physical vulnerability map of roads and rails infrastructures was generated. In spatial analysis, line statistics calculate a statistic (e.g. mean) on the attributes of lines in a circular neighbourhood around each output cell (ESRI, 2011).

4.1.5 Quadrat analysis. The specific use of quadrat analysis in this study dealt with the detection of point patterns of infrastructure connections 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. In generating the Quadrat (Q) subsets, a fishnet was created in ArcGIS 10 and spatially joined the infrastructures nodes or heritage sites with the intersect tool into the fishnet to count its number per Q subset. This method enabled to evaluate the distribution of point locations of infrastructure connections or heritage sites distribution by examining the density (expressed as the number of infrastructure connections or heritage sites per quadrat) changes over space (Wong and Lee, 2005). The infrastructure node density and heritage site density were further analyzed 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.

4.1.6 Spatial analysis 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. 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 analysis 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 the attribute table holding the sum of all hazard incidents for each unique location. The results of the analysis were further analyzed with spatial autocorrelation techniques to cluster the weighted hazard points and interpolated with IDW technique to generate the hazard maps.

4.1.7 Modeling with spatial autocorrelation. Noticeably from previous discussions, spatial autocorrelation techniques played a significant role in the process of standardization to some data sets. Using ArcGIS 10, this study specifically applied the techniques known as Global Moran’s I and Cluster and Outlier Analysis (i.e. Anselin Local Moran’s I). 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). The initial outputs generated from the spatial autocorrelation analyses were summarized in raster using the IDW method of point data interpolation. The generated raster maps were then carefully analyzed to assign categorized values for each indicating variable that generally explain perceived level of flood risk (i.e. 1 – low, 2 – moderate, 3 – high, and 4 – very high).

4.1.8 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 the desired number bring uncertainty in assigning the ordinal values for the perceived flood risk during the assessment process. Using ArcGIS 10, the hot spot analysis was then operationalized to address this issue and applied in the exposure assessment of heritage sites.

4.2 Calculating Bayesian joint conditional probability weights

Gregoire and Konieczny (2006) described that computer-based applications require various conflicting sources of information to be aggregated to form a global contradiction-free system. One of the potential methods that can be used to implement this exercise is the probabilistic causal modeling that facilitates 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 CA capacity based on Bayesian theorem.

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 characterizing 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).

The weight values used in aggregating the indicating variables of hazard, vulnerability, and exposure using the weighted overlay analysis in ArcGIS 10 were calculated using the following equation:

$$P(FR_i \backslash V_i) = \frac{Pmax(FR_i \cap V_i)}{\sum_{i=1}^{n} Pmax(FR_i \cap V_i)} \tag{5}$$

where:

FR is the flood risk represented by flood hazard as an *a priori* 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; and

n is the number of indicating variables.

The results of the calculations are presented in Table I.

4.3 Self-organizing neural network

Various "intelligent" systems have 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). One of the relatively new computational tools that have found extensive application in solving various complex real-world problems is known as Artificial Neural Networks (ANNs) (Basheer and Hajmeer, 2000).

Artificial neural networks (ANNs) 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 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).

The extensive applications of artificial neural networks in various studies include, but not limited to, the prediction of food pathogen *Escherichia coli* (Gosukonda *et al.*, 2015), generation of a contour map of the ground conductivity (Kalogirou *et al.*, 2015), river water quality modeling (Sarkar and Pandey, 2015), prediction of gas storage capacities in metal

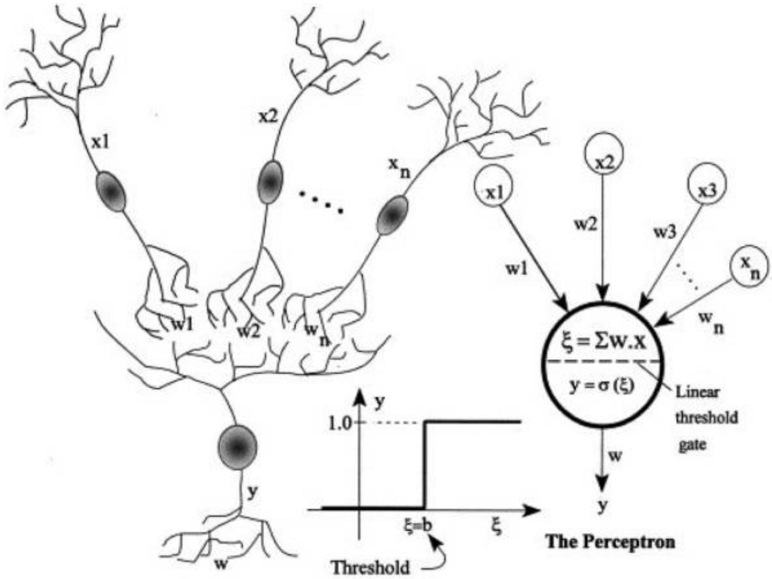


Figure 4. The analogy between artificial neuron and biological neuron

Source: Basheer and Hajmeer (2000). Reprinted with permission

organic frameworks (Yildiz and Uzun, 2015), thermal analysis of heat exchangers (Mohanraj *et al.*, 2015) and flood forecasting (Elsafi, 2014).

In risk management, the main question that confronts DRR managers generally involves knowledge of how to integrate disaster risk considerations in sustainable development policies such as CA at the federal, state or local level and the systematic incorporation of preparedness, mitigation, response and recovery measures. The advent of GIS has made mapping of flood risk and CA capacity variables easier by providing tools that manipulate these data and allow their integration. However, leaping directly into data integration without initial relational assessment of indicating variables will lead into less accurate modeling and simulation result. In using prediction models in risk management, the most important part is the correct selection of input data especially when they have high variance (Nasri, 2010). Pavlin *et al.* (2010) further emphasized 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. This study proposed to address the issues by using spatial analytical tools in combination with self-organizing neural network (SONN). The approach was implemented by exploring the multi-parametric assessment of flood risk and CA capacity with Kohonen's self-organizing map (KSOM/SOM). The standardized variables for flood risk and CA capacity variables (Table I) were imported in the MATLAB workspace.

A subtype of artificial neural network (ANN) that is particularly useful for visualization of highly dimensional data is the Kohonen self-organizing map (KSOM/SOM) (Mele and Crowley, 2008). A self-organizing map consists of a competitive layer that allows classification of data sets with any number of dimensions into as many classes as the layer has neurons, which are arranged in a 2D topology (The Mathworks, Inc., 2013). In this study, we operationalized the SOM with the input layers representing the flood risk and CA capacity indicating variables, neuron computation and output layer, and a map of clustered variables (Mele and Crowley, 2008) as shown in Figure 5. 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 visualization, data analysis and numeric computation (The Mathworks, Inc., 2013).

From Table I, a total of 37 indicating variables that had been standardized were subsequently used in the SOM analysis: 5 for hazard, 7 for physical vulnerability, 17 for social vulnerability and 8 for exposure. In analyzing these variables, vulnerability assessment of individual critical infrastructure had given particular emphasis. These infrastructures include electricity, roads and rails, sewerage, stormwater and water supply.

The first step in analyzing data in MATLAB was to import the standardized variables in previously saved Tagged Image File Format (TIFF). The imported variables were displayed in a 1000 × 1000 matrix or a rectangular array of numbers with row and column values. These numerical values represent the perceived level of flood risk (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 × 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 represents the flood risk and CA capacity variables;

c is the complete set of variables in a single n × m array;

n is the number of rows; and

m is the number of columns represented by 37 variables.

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

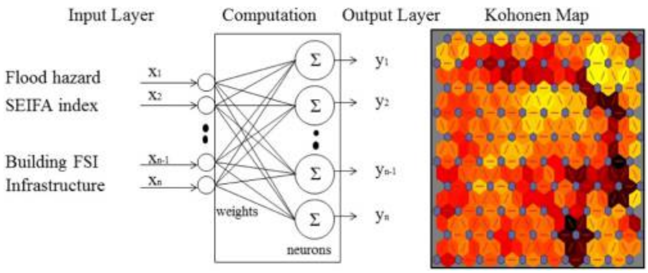


Figure 5. The conceptual self-organizing map used in the study

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.

4.4 Quantification of flood risk and climate adaptation capacity metrics

In the geospatial domain, data aggregation can be operationalized using the weighted overlay analytical tool which is available in several GIS software such as ArcGIS. From Table I, the values shown were the calculated Bayesian joint conditional probable weights using equation (5). The weighted overlay technique was used to produce the hazard, vulnerability and exposure indices. Various studies and applications of weighted overlay modeling were developed such as determining the best locations for artificial recharge of groundwater (Riad *et al.*, 2011), geothermal favorability mapping (Procesi *et al.*, 2015), evaluating landslide hazard zonation (Raghuvanshi *et al.*, 2015), evaluating soil suitability for cotton farming (Walke *et al.*, 2012) and detecting flood hazard in urban areas (Ozkan and Tarhan, 2016), among others.

After having generated the hazard, vulnerability and exposure indices, the fuzzy gamma overlay analysis was performed to derive the flood risk index maps. The fuzzy gamma overlay operation was chosen in this study to resolve the confusion as to which risk equation [see equations (1) to (3)] 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 analyzing 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 by specific infrastructure and then the integrated infrastructure. Operationalizing equation (4) through the raster calculator tool in ArcGIS 10, the CA capacity index maps were generated.

5. Results and discussions

5.1 Generated self-organizing map planes by infrastructure assets and corresponding Bayesian joint conditional probable weights

The unified matrix (U-matrix) and the component planes that represent individual variables are the two separate parts of the SOM display (Mele and Crowley, 2008). In this study, we emphasized the importance of component planes (shown in Figure 6(a)-(f) for individual indicating variables as specified in Table I. The color codes correspond to the actual numerical values for the input variables that are referenced in the vertical scale bars adjacent to each SOM plane (Mele and Crowley, 2008). Shown in Figure 6(a)-(f) are the generated SOM planes of all indicating variables by infrastructure asset and integrated infrastructure assets. Dark red to black colors show high values, while light yellow corresponds to low values. The relationships between and among each of the flood risk and CA capacity indicating variables were visualized by comparing the color patterns for individual SOM plane. Through this approach, the relationships between and among all the variables can be examined simultaneously or in pair-wise combinations (Mele and Crowley, 2008).

In this study, we examined 30 indicating variables to assess the flood risk and CA capacity of electricity, roads and rails, sewerage, stormwater, water supply infrastructures and the combination or integration of those infrastructures (Table I). 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. A good and easily

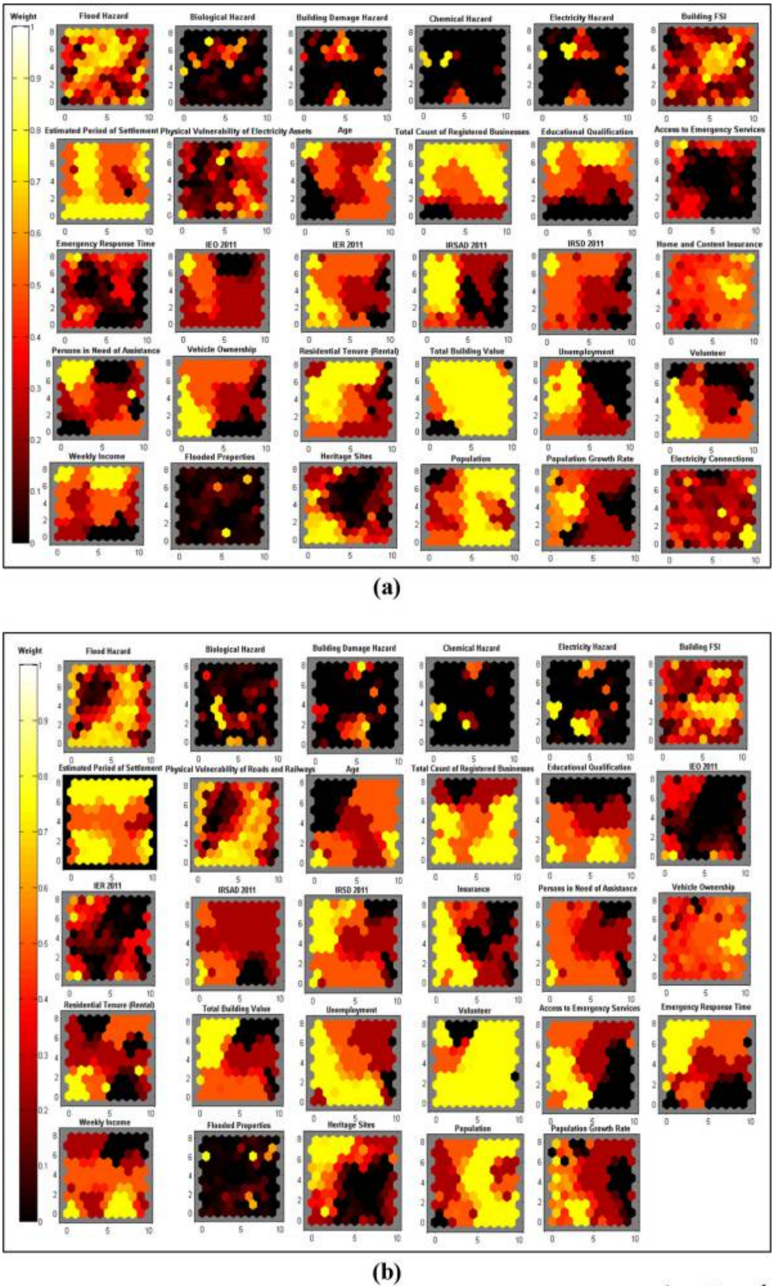


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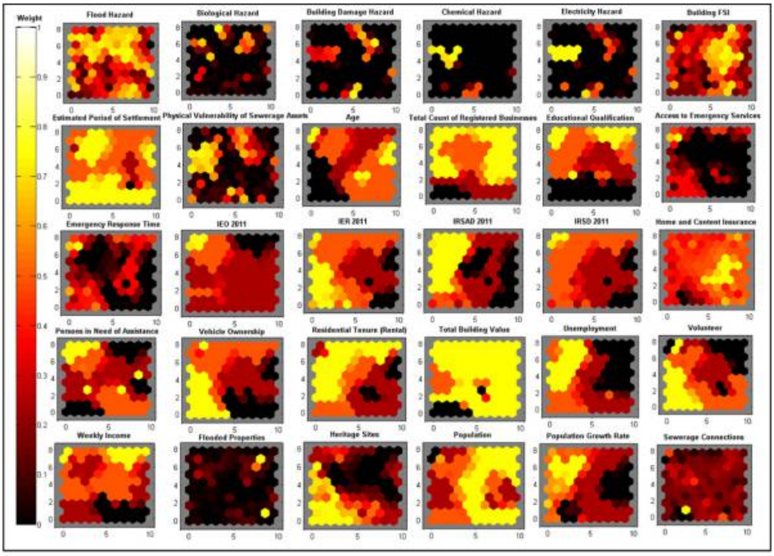
Figure 6.
The generated SOM planes of indicating variables by infrastructure asset



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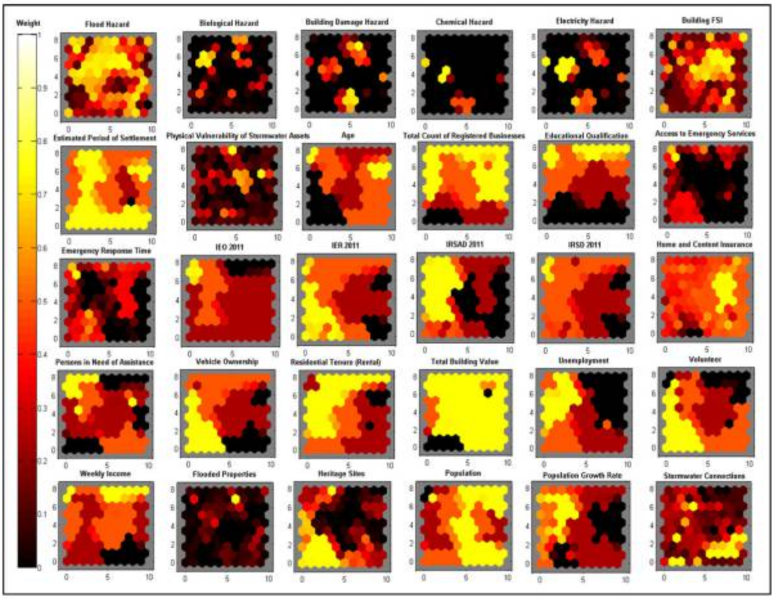

(d)

Figure 6.

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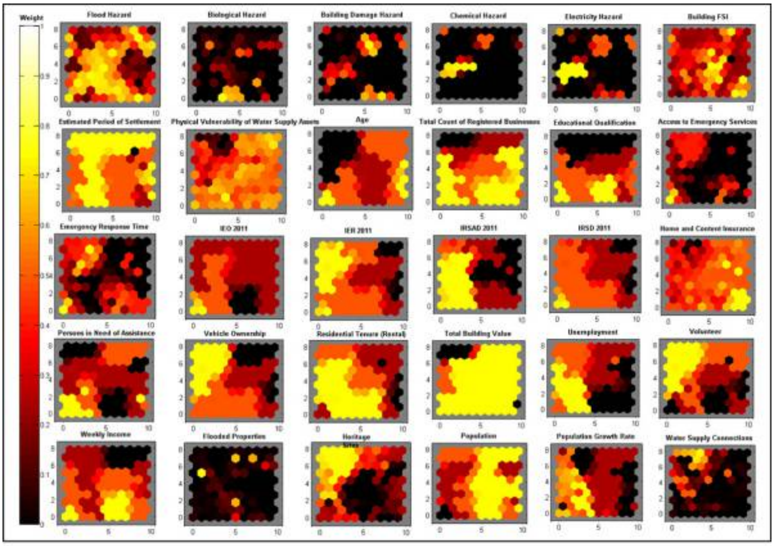

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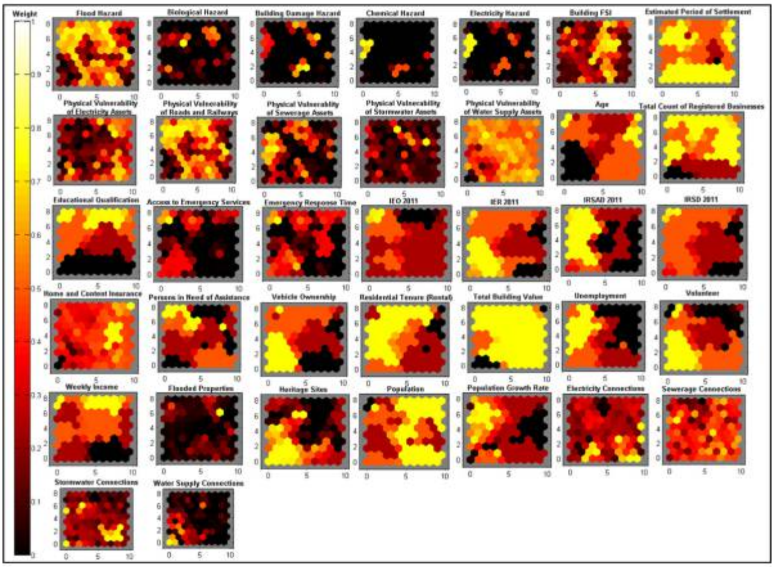

(f)

Notes: (a)Electricity network; (b) road and rail networks; (c) sewerage network; (d) stormwater network; (e) water supply network; and (f) integrated infrastructures

Figure 6.

distinguishable example can be seen by examining the relationship between flood hazard and the heritage sites from Figure 6(b). In general, the visual pattern shows an inverse relationship or dissimilarity between these two variables – the actual numerical values in the flood hazard's SOM plane increase diagonally from lower right corner to upper left corner while the values in the heritage site's SOM plane decrease of the same direction. Hence, heritage site indicating variable was removed from further analysis and excluded as a component in the vulnerability assessment of road and rail infrastructures.

In this manner, all indicating variables marked as "x" from Table I were excluded from further analysis because they have general patterns dissimilar to flood hazard. (Note: "NA" in Table I refers to variables not applicable in the analysis). In general, the excluded variables were observed to have lower weights that concentrate at the center of their respective SOM planes which are in reverse to the general pattern showcased by flood hazard variable. However, when all these indicating variables were integrated [Figure 6(f)], pair-wise comparison showed that all indicating variables were included for further analysis because they have not shown clear patterns of dissimilarity against the flood hazard indicating variable.

Furthermore, Table I summarizes the results of the analysis showing that 27 of 30 indicating variables from electricity, roads and rails, sewerage and stormwater; 28 of 30 from water supply; and 30 of 30 from integrated infrastructures were selected or included in the quantification of flood risk and CA capacity metrics.

5.2 Flood risk and climate adaptation capacity models

Applying equations (3) and (4) through the use of the raster calculator tool in in conjunction with fuzzy gamma overlay in ArcGIS 10, we generated the flood risk and CA capacity index maps (Figures 7 and 8).

Figure 9 summarizes the results shown in Figures 7 and 8 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 color-coded vertical columns 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, we observed that the areas being occupied with very high flood risk are larger than the areas being occupied with low adaptation capacity across infrastructure categories. This observation was also demonstrated when the critical infrastructures were integrated. We conclude that this inverse relationship of flood risk and adaptation capacity may signify 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, we observed 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 means that in general, areas of low adaptation capacity are bounded within the areas of very high flood risk. This trend was also exemplified when the critical infrastructures were integrated. We further infer that the significance of understanding this relationship may demonstrate that flood risk outweighs the CA capacity of the study area. In this study, we referred the integration of flood risk and CA capacity modeling as *Flood Risk – Adaptation Capacity Index – Adaptation Strategies (FRACIAS) Linkage/Integrated Model*. The details and potential applications of this model is fully discussed in the following sub-sections.

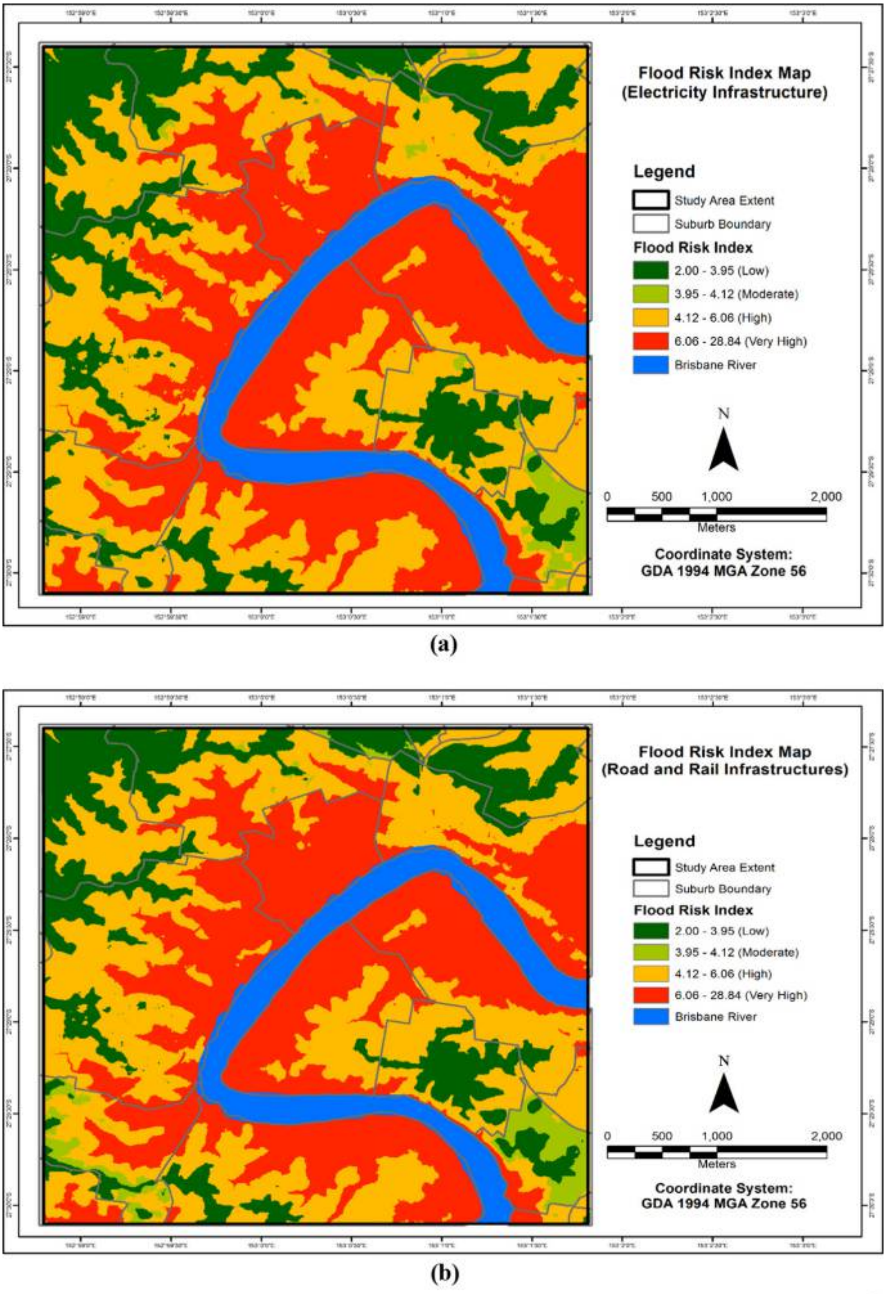

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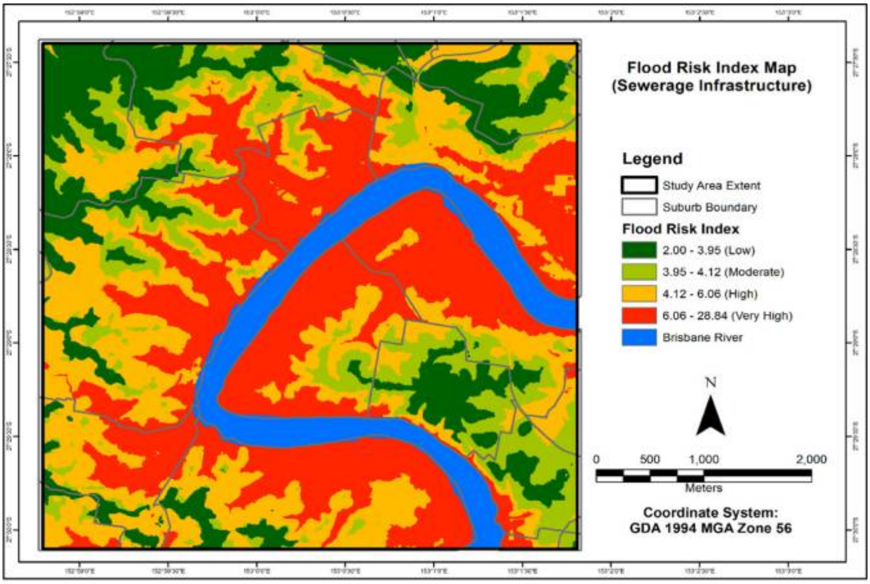
Figure 7.
The flood risk index maps by infrastructure asset



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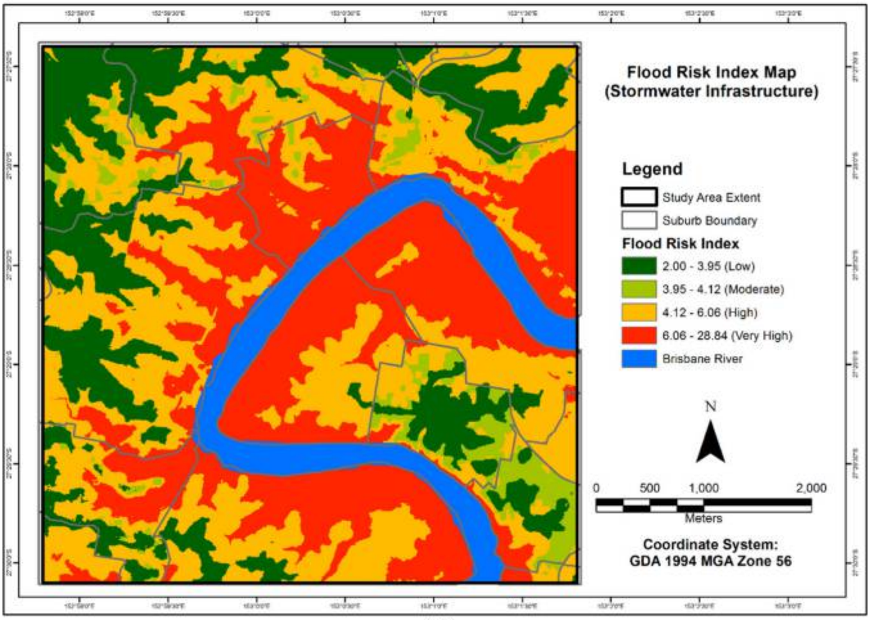

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Figure 7.

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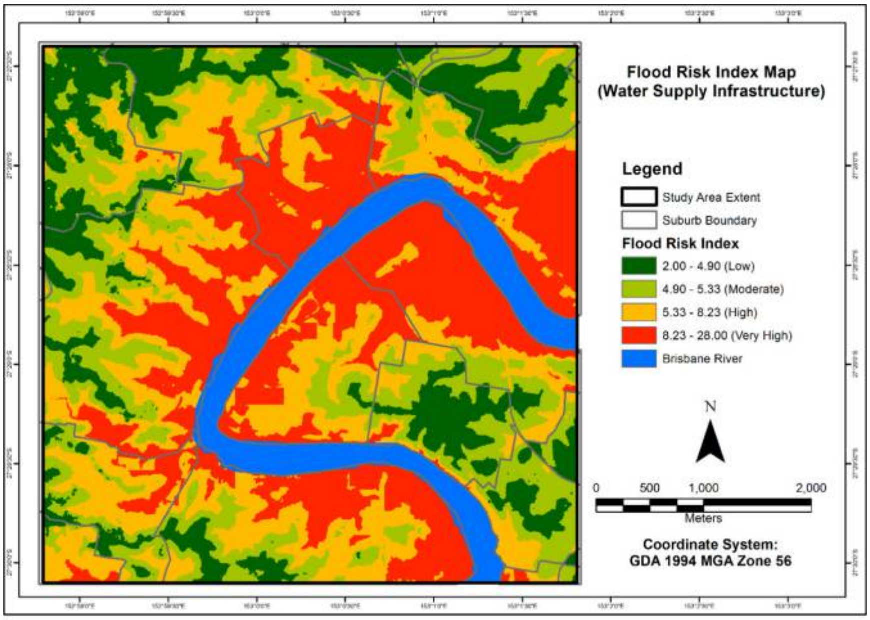

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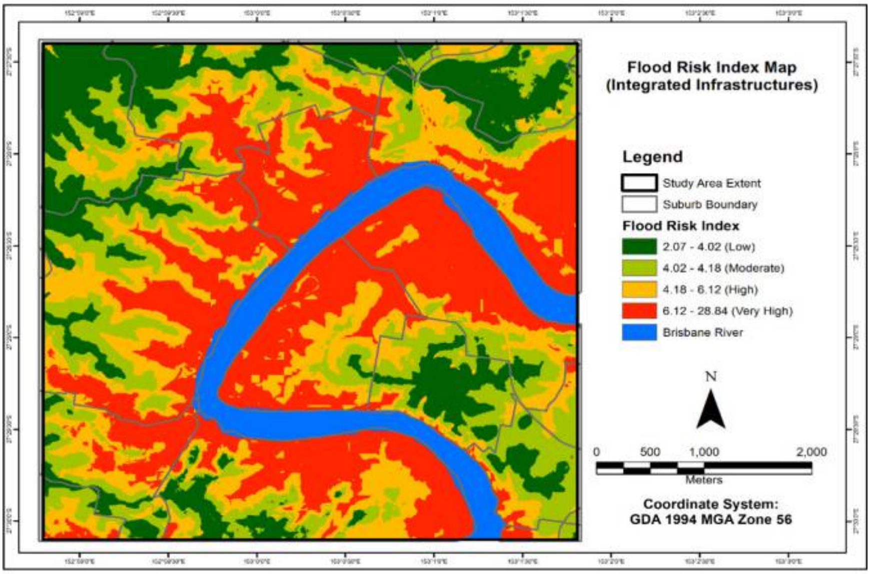
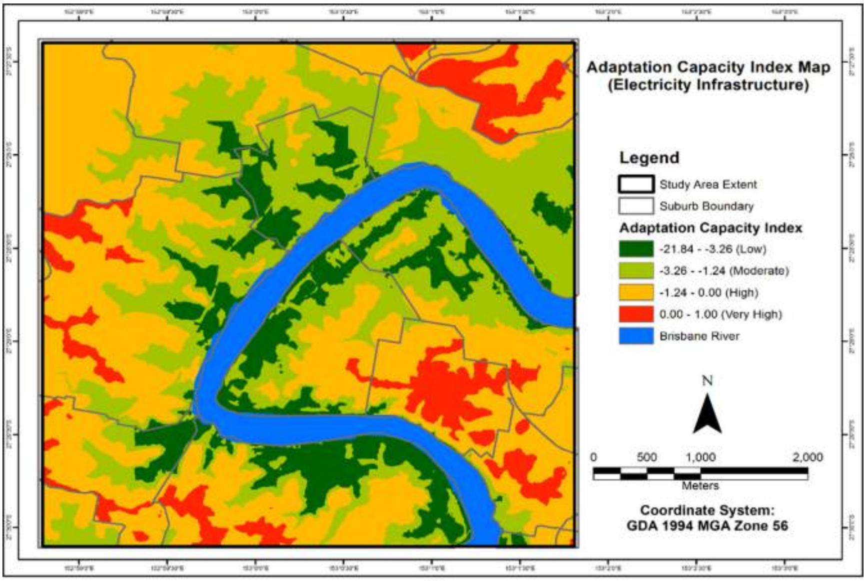


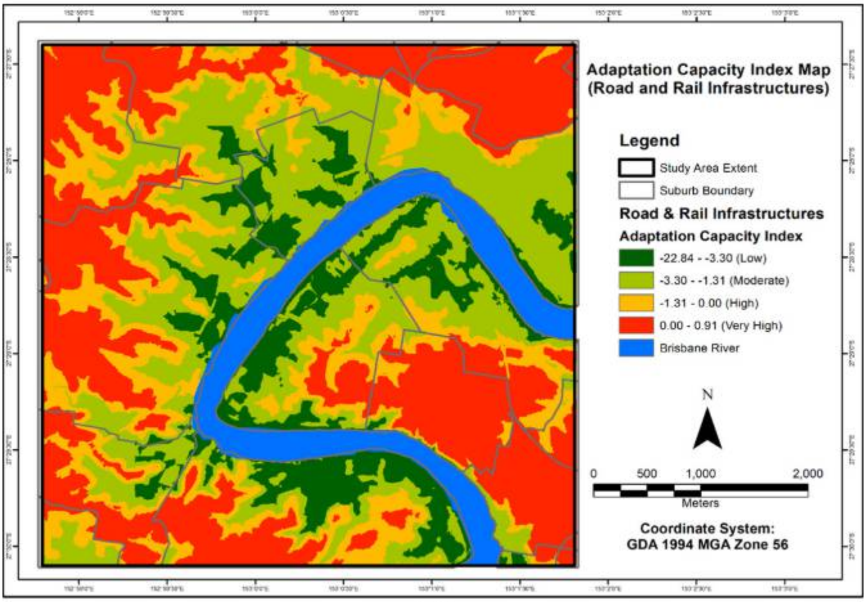
(f)

Notes: (a) Electricity network; (b) road and rail networks; (c) sewerage network; (d) stormwater network; (e) water supply network; and (f) integrated infrastructures

Figure 7.



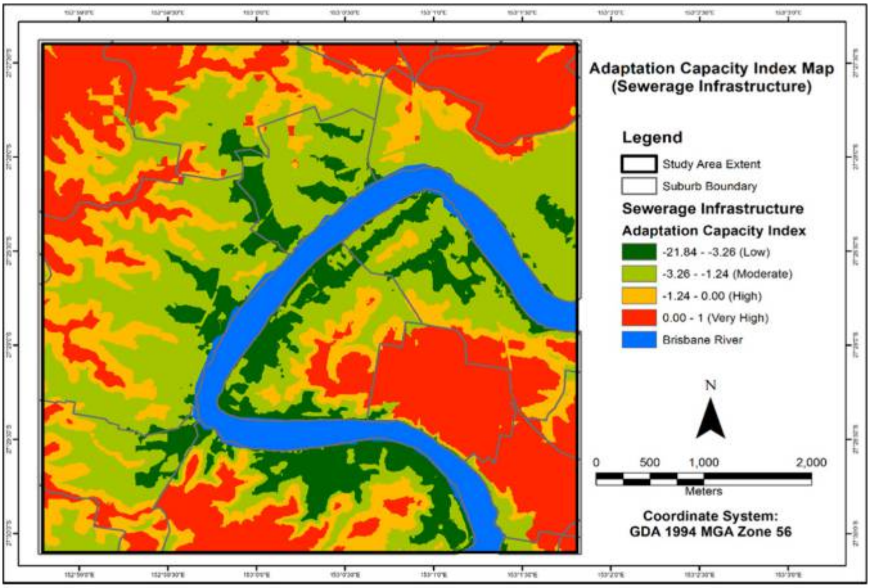
(a)



(b)

Figure 8.
The CA capacity index maps by infrastructure asset

(*continued*)



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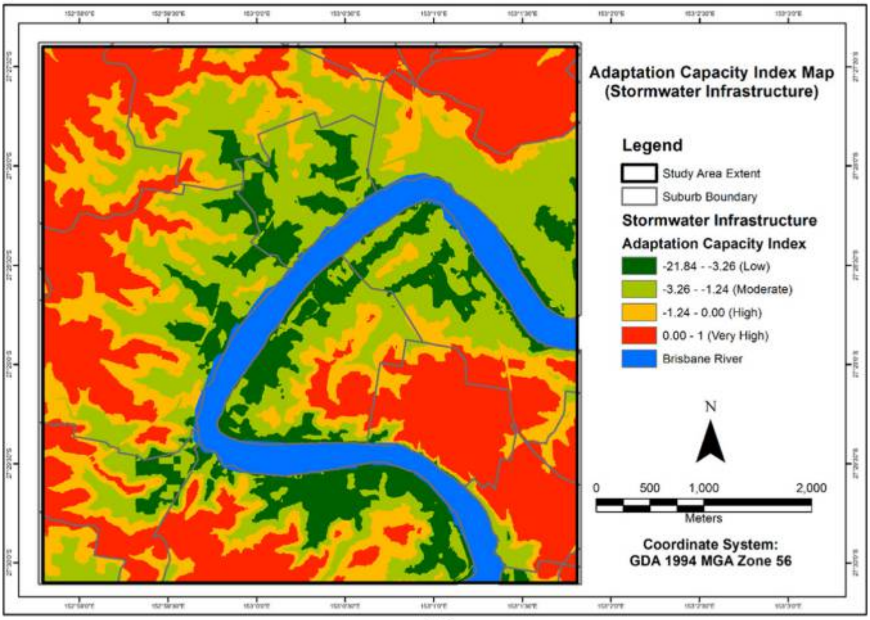
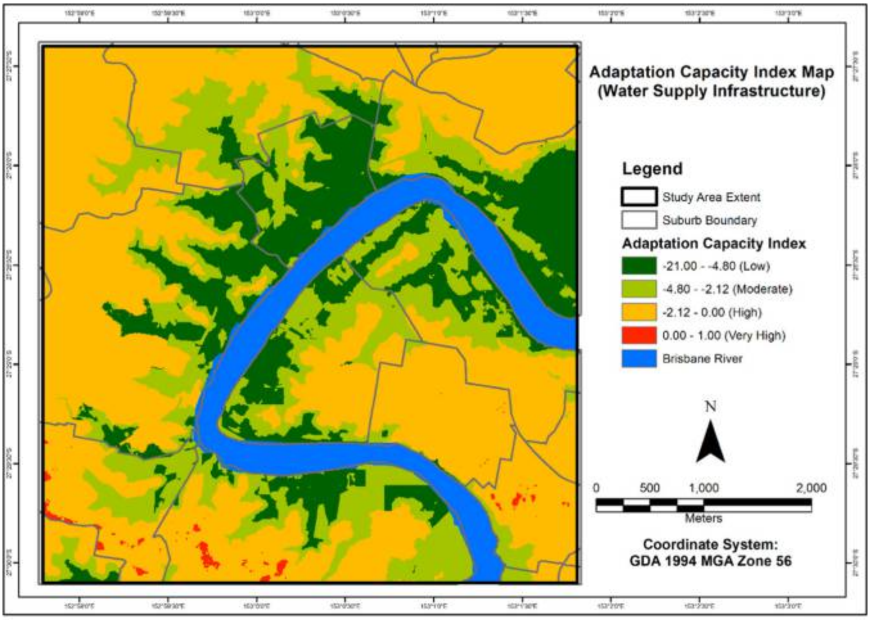


(d)

(continued)

Figure 8.



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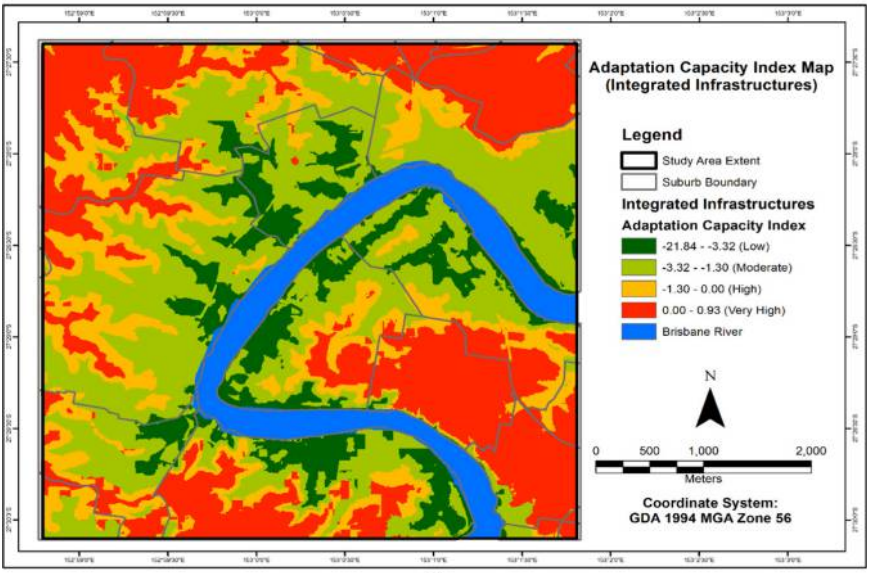
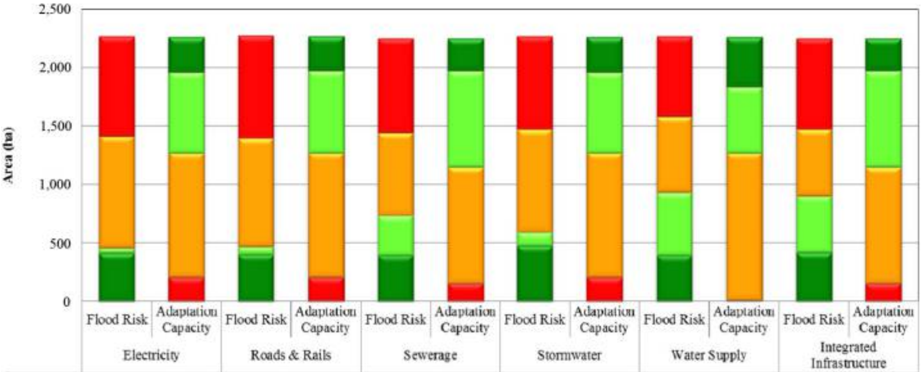


(f)

Figure 8.

Notes: (a) Electricity network; (b) road and rail networks; (c) sewerage network; (d) stormwater network; (e) water supply network; and (f) integrated infrastructures



	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 9. The area coverage of flood risk and CA capacity by infrastructure asset

5.2.1 Flood risk – adaptation capacity index – adaptation strategies linkage/integrated model. In the past, flood risk and CA capacity assessments in certain areas had been treated separately. Applied in this study, FRACIAS linkage/integrated model used GIS in generating not only the level of risks that the urban area and critical infrastructures had been exposed to flood but also its level of capacity to adapt. Both levels (i.e. flood risk and adaptation capacity) were described through the indices/metrics generated from GIS analysis. As a tool for high level analyses, this approach identified DRR measures or CA strategies (i.e. shown in Figure 10) to enable urban communities and critical infrastructure industries to better prepare and mitigate future flood events. Essentially, this model can also be applied to other sectors (e.g. agriculture, forest resources, etc.) in natural environments aside from critical infrastructures in urban settings.

As summarized from Figures 7 and 8, Figure 10 shows the proportional values of areas being occupied by flood risk (in yellow rows) and CA capacity (in green rows) with corresponding indices/metrics by descriptive level across infrastructure category.

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
Adaptation capacity

Figure 10. The index/metric values by infrastructure asset and corresponding DRR measures/CA strategies by level of flood risk and CA capacity

Interested to look at Figure 10 are the CA capacity metrics (in green rows) against the flood risk metrics (in yellow rows). Analyzing the matrix by column, for example, we observed that the percentage of areas occupying very level of flood risk is larger than the percentage of areas being occupied by very high adaptation capacity. We further detected that seven per cent (7 per cent) of the study area (approximately 158 ha) exhibited positive adaptation capacity metrics (i.e. >0 to maximum of 1). We infer that 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 favorable physical condition (e.g. higher elevation), but the socio-economic resources inhibit the adaptation to climate risk.

Moreover, we observed that majority of the study area (93 per cent) revealed negative adaptation capacity metrics (i.e. minimum of -22.84 to < 0), which indicate that the capacity of the urban community requires further deliberation as to how CA 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 are not enough to increase climate resilience of the urban community and critical infrastructures (Espada *et al.*, 2012, 2013b, 2013c). Through this finding, we further observed that the resources of the community are outbalanced by approximately 23 units taking zero as the break-even metric.

The above findings would imply that the study area requires a range of DRR or CA strategies that would increase community and critical infrastructure resilience as shown in Figure 10. Adopted from (QRA, 2011), the four phases of DRR or CA strategies identified to increase community resilience include mitigation, preparedness, response and recovery. On the other hand, some specific DRR measures and CA strategies are discussed in the following sections.

5.2.2 Application of FRACIAS linkage/integrated model to natural disaster risk reduction and climate adaptation strategies. According to Australian Government – Department of Transport and Regional Services (DOTARS), the response measures on floods, coastal inundation, storms and cyclones in the country are not sufficient to assist the economic and social recovery of the communities (Department of Transport and Regional Services, 2002). 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 emphasized the importance of linking the flood risk and adaptation capacity metrics to identify flood priority areas for funding support to increase communities' climate resilience.

The above issues would further imply that the study area requires a range of DRR or CA adaptation strategies that would increase community and critical infrastructure resilience. Adopted from Queensland Reconstruction Authority's (QRA) (2011), four phases of DRR, the broad adaptation strategies identified to increase community resilience include mitigation, preparedness, response and recovery. Looking back at Figure 10 and Figures 7 and 8, their physical significance suggests to consider the following DRR measures and/or CA strategies:

- mitigation on areas of low flood risk or very high CA capacity;
- mitigation to preparedness on areas of moderate flood risk and high CA capacity;
- mitigation to response on areas of high flood risk and moderate CA capacity; and
- mitigation to recovery on areas of very high flood risk and low CA capacity.

Some examples of DRR and CA strategies and the implications of linking them together are discussed in the following section/sub-sections.

5.2.3 Implications of integrating disaster risk reduction and climate adaptation in flood prone areas. In this section, we emphasized the implications of linking DRR measures (i.e. mitigation, preparedness, response and recovery) with CA in flood prone areas specifically in the core suburbs of Brisbane City and, in general, also in some affected by the January 2011 flood in Queensland, Australia.

5.2.3.1 Mitigation measures/strategies. The design and provision of more resilient and new or updated infrastructures and services are key aspects of disaster mitigation. Hence, this is also the opportunity to take into account CA. Examples, issues and recommendations to integrate disaster mitigation with CA are provided in the subsequent paragraphs.

During the 2010/2011 floods in Queensland, some residents and residential properties were isolated by floodwaters and some commercial properties (e.g. shopping centers) were inundated [Flegg, 2011; Queensland Floods Commission of Inquiry (QFCI), 2012]. The flood risk and adaptation capacity maps shown in Figures 7 and 8 can assist identify highly vulnerable critical infrastructures on areas of very high flood risk and low adaptation capacity. The models can also help identify the areas requiring flood mitigation measures and CA interventions for consideration in the future planning schemes. For examples, the minimum floor levels of habitable and non-habitable rooms of residential houses should be built to specified level of immunity [Brisbane City Council (BCC), 2011a, 2011b; Queensland Floods Commission of Inquiry (QFCI), 2012] and should include consistency in height between the proposed building and the existing streetscape [Ipswich City Council (ICC), 2012; Queensland Floods Commission of Inquiry (QFCI), 2012]. The design of residential buildings should also include the use of water resistant materials of a non-structural nature [Brumby, 2011; Queensland Floods Commission of Inquiry (QFCI), 2012]. Moreover, Reynolds (2011) and the Queensland Floods Commission of Inquiry (QFCI) (2012) recommended the setting of a mandatory minimum freeboard level across the state or a higher freeboard in cases of high measure of uncertainty surrounding the estimated flood level.

To increase community resilience, buildings should consider the construction of walls out of modern fibrous cement, used acrylic water-based paint, raised the height of electricity supply points and used flood resistant floor materials [White, 2011; Queensland Floods Commission of Inquiry (QFCI), 2012]. The location of electricity assets such as switchboards and back-up power supplies was likewise recommended to consider in building design to mitigate the effects of future floods [Queensland Floods Commission of Inquiry (QFCI), 2012]. Conduits of electrical cables should also be sealed and waterproofed [Sun, 2011; Queensland Floods Commission of Inquiry (QFCI), 2012] to prevent stormwater from flowing into the buildings' basements.

To significantly minimize the risk posed by flood to lives and properties, some local governments in Queensland currently operate the "property buy-back" and "land swap" programs. The former is a voluntary selling of privately owned properties which are prone to flooding to the local or state government and re-use such land for purposes other than residential [Lord Mayor's Taskforce on Suburban Flooding, 2005; Brisbane City Council

(BCC), 2011a, 2011b; Queensland Floods Commission of Inquiry (QFCI), 2012]. The land swap program, on the other hand, allows eligible property owners to "swap" their flood hazard land for part of the land situated above the 2011 flood levels which was purchased by the local government [Simmonds, 2011; Queensland Floods Commission of Inquiry (QFCI), 2012]. The options to consider in decision-making include the voluntary implementation of these programs to areas with very high flood risk or to increase the level of adaptation capacity on these areas.

The aforementioned disaster mitigation strategies are examples of structural and non-structural measures. However, those measures focused predominantly on sudden onset of extreme events such as floods; hence, the DRR programs in flood prone areas such as the core suburbs of Brisbane City should be taken into account the CA strategies by increasingly paying attention to the likely occurrence or intensification of flood hazard due to climate change (Birkmann and von Teichman, 2010) and climate variability.

5.2.3.2 Preparedness measures/strategies. Community education, training, awareness, information management and early warning are some significant components in risk reduction and CA to ensure that the community is prepared and able to manage the consequences of a disaster and extreme climate events. Unfortunately, flood risk information in preparation for the January 2011 was often not publicly available; i.e. less than 50 per cent of local councils in Queensland provide flood risk information (van den Honert and McAneney, 2011). While the National Flood Information Database (NFID) is the primary source of flood information and digital terrain maps for the public, it does not include every property at risk and commonly not available in Queensland (van den Honert and McAneney, 2011). The hazard information (e.g. early warning systems) should be developed beyond the sudden-onset of event by integrating the likely occurrence of risk which will be intensified by climate change (Birkmann and von Teichman, 2010) such as emerging changes of riverine flood levels due to sea level rise.

5.2.3.3 Response measures/strategies. The Emergency Management Queensland – Department of Community Saftey (EMQ-DCS) (2011) defined disaster response phase as the process of conducting activities and appropriate measures necessary to respond to an event with immediate relief and support.

The direct aftermath of the January 2011 prompted the Brisbane City Council to activate the Local Disaster Coordination Centre (LDCC), used its resources and worked in conjunction with emergency services, police, fire and rescue, other government departments and agencies, other local councils and not-for-profit organizations [Brisbane City Council (BCC), 2011a, 2011b]. During this phase, the Council's tasks comprised the following: restoration of essential services, clearing of major and arterial roads, restoration of public transport and assessment of damaged household and business properties [Brisbane City Council (BCC), 2011a, 2011b]. In this phase, while not directly beneficial, the integration of CA strategies can be achieved by considering information about anticipated climate-related changes and the development of flexible structures into response strategies such as humanitarian assistance (Birkmann and von Teichman, 2010), volunteer works and socio-psychological support to recover from prolonged flood isolation.

5.2.3.4 Recovery measures/strategies. In disaster recovery phase, the 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 [Emergency Management Queensland – Department of Community Saftey (EMQ-DCS), 2011]. In Australia, the natural disaster relief and recovery assistance is provided through the joint Australian and State Government's Natural Disaster Relief and Recovery Arrangements

(NDRRA) (Australian Government Disaster Assist, 2014). Under this arrangement, the Federal Government funds 75 per cent of all infrastructure reconstruction costs in the event of natural disaster; however, this scheme is not compulsory for State Governments to take insurance for its infrastructure assets such as the case of Queensland (van den Honert and McAneney, 2011).

The integration of CA strategies during this phase, for example, includes the consideration of taking insurance cover for infrastructure assets and medical care programs for new health threats due to climate-related extreme events and natural hazards (Birkmann and von Teichman, 2010).

6. Summary, conclusion and recommendations

The framework described in this study has addressed the complementary roles of GIS, flood risk assessment and CA capacity assessment. In this context, we summarized this framework by bringing together the goals of these three (3) components as follows (Figure 11):

- GIS – Flood risk assessment interlink (a) – characterized by integrating the temporal and spatial information within the context of natural hazard, vulnerability and exposure of particular geographical area at local, national or global scale;
- GIS – CA capacity assessment interlink (b) – characterized by integrating the temporal and spatial information taking into consideration the human, social and environmental capacity within the context of future climate changes;
- Natural disaster risk assessment – CA capacity assessment interlink (c) – characterized by analyzing the short-term and long-term effects of disaster risks including projected changes of climate; and
- Flood risk-adaptation capacity index – Adaptation strategies (FRACIAS) linkage/integrated model (d) – characterized as a system that allows the integration and analyses of disaster risks (e.g. flood risk), CA capacity and adaptation strategies of a particular geographical area including its critical sectors (e.g. urban community and its infrastructures).

Hence, the main contribution of this study was the integration of DRR and CA which had been treated separately in the past. Identified in this study as *Flood Risk-Adaptation Capacity Index-Adaptation Strategies (FRACIAS) Linkage/Integrated Model*, the model specifically allows the identification of areas characterized by very high flood risk and low

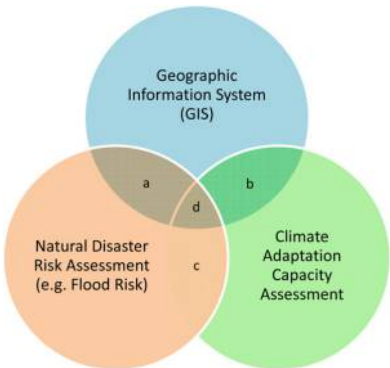


Figure 11.
The FRACIAS linkage/integrated model

adaptation capacity. Then, we identified the corresponding DRR and CA strategies for urban areas and critical infrastructures in the study area.

By applying the FRACIAS linkage/integrated model in the context of flood risk and CA capacity assessments, we established a framework for enhancing measures and strategies to increase urban community and critical infrastructure resilience to flood risk and climate-related events. Specifically, the FRACIAS linkage/integrated model has been characterized by a number of features that include:

- An emphasis is given on the transformation, standardization and appropriate selection of indicating variables in the flood risk and CA capacity assessments rather than simply doing the risk assessment exercise without examining the input variables.
- Grounding in the quantitative description of flood risk and CA capacity levels of urban community and its critical infrastructures through GIS-generated indices. In general, areas of high level of flood risk have low level of adaptation capacity.
- Incorporation of DRR measures (i.e. mitigation, preparedness, response and recovery) that would help increase urban community and critical infrastructure resilience from flooding, stressing the need to improve risk reduction measures by integrating CA strategies.
- The integrated model allows the development of policies and measures to both address the short-term effects of January 2011 flood and the long-term impacts of climate-related events.

While the framework in this study was obtained through a robust approach, the methods used in generating the integrated model are recommended for further examination to consider the following:

- analyzing and incorporating the impacts of economic growth, population growth, technological advancement, climate and environmental disturbances and climate change; and
- applying the methods in assessing the risks to natural environments such as in agricultural areas, forest protection and production areas, biodiversity conservation areas, natural heritage sites, watersheds or river basins, parks and recreation areas, coastal regions, etc.

References

Abukhater, A. (2011), *GIS-Based Community Risk Assessment*, ESRI, CA.

Australian Bureau of Statistics (ABS) (2008), "Feature article 4: natural disasters in Australia", available at: www.abs.gov.au/ausstats/abs@.nsf/94713ad445ff1425ca25682000192af2/fecb2ab6de16171eca2570de0005871b!OpenDocument (accessed 15 July 2011).

Australian Government Disaster Assist (2014), "Diaster assist: information about recovery assistance following a disaster", available at: www.disasterassist.gov.au/PreviousDisasters/StateandTerritories/Pages/QLD/SouthernQueenslandflooding(NovemberDecember2011).aspx (accessed 14 June 2016).

Baer, E. (2008), "Teaching floods and flooding quantitatively: teaching quantiative skills in the geoscience", available at: http://serc.carleton.edu/quantskills/methods/quantlit/floods.html (accessed 30 June 2011).

Basheer, I.A. and Hajmeer, M. (2000), "Artificial neural networks: fundamentals, computing, design, and application", *Journal of Microbiological Methods*, Vol. 43 No. 1, pp. 3-31.

Bell, H. (2010), *Understanding and Assessing Disaster Risk*, Pacific Disaster Center, Taipei.

Birkmann, J. and von Teichman, K. (2010), "Integrating disaster risk reduction and climate change adaptation: key challenges – scales, knowledge, and norms", *Sustainability Science*, Vol. 5 No. 2, pp. 171-184.

Bosello, F., Carraro, C. and De Cian, E. (2009), *An Analysis of Adaptation as Response to Climate Change*, Copenhagen Consensus Center, Frederiskberg.

Brisbane City Council (BCC) (2011a), *Be Flood Wise Fact Sheet*, Brisbane City Council, Brisbane City.

Brisbane City Council (BCC) (2011b), *Brisbane River Flooding Disaster January 2011 Concept for Recovery*, Forward Planning Group, Local Disaster Coordination Centre, Brisbane City Council, Brisbane City.

Brisbane City Council (BCC) (2012), *Brisbane Long Term Infrastructure Plan 2012-2031*, Brisbane City Council, Brisbane City.

Brule, J. (1985), "Fuzzy systems-a tutorial", available at: www.austinlinks.com/Fuzzy/tutorial.html (accessed 12 November 2011).

Brumby, G. (2011), *Statement of Glen Brumby*, Queensland Floods Commission of Inquiry, Brisbane City.

Bureau of Transport and Regional Economics (BTRE) (2002), *Benefits of Flood Mitigation in Australia*, Bureau of Transport and Regional Economics, Canberra, Australian Capital Territory.

Cavan, G. and Kingston, R. (2012), "Development of a climate change risk and vulnerability assessment tool for urban areas", *International Journal of Disaster Resilience in the Built Environment*, Vol. 3 No. 3, pp. 253-269.

Collins, B., Balmforth, D., Rooke, D., Scott, J., Wilkinson, M., Davies, P., Warry, P. and Fox, T. (2011), *Infrastructure, Engineering and Climate Change Adaptation*, The Royal Academy of Engineering, London.

Department of Transport and Regional Services (2002), "Natural disasters in Australia: reforming mitigation", *Relief and Recovery Arrangements – A Report to the Council of Australian Governments by a High Level Officials's Group*, Australian Government Department of Transport and Regional Services, Canberra.

Downing, T. (2002), *Concepts of Vulnerability: Climate Change Vulnerability and Adaptation*, Third World Avademy of Sciences, Trieste.

Elsafi, S.H. (2014), "Artificial neural networks (ANNs) for flood forecasting at Dongola station in the river Nile, Sudan", *Alexandria Engineering Journal*, Vol. 53 No. 3, pp. 655-662.

Emergency Management Queensland – Department of Community Saftey (EMQ-DCS) (2011), *Queensland State Disaster Management Plan 2011*, State of Queensland – Department of Community Safety, Brisbane.

Espada, R., Apan, A. and McDougall, K. (2012), *Spatial Modelling of Adaptation Strategies for Urban Built Infrastructures Exposed to Flood Hazards*, Surveying and Spatial Sciences Institute, Brisbane City.

Espada, R., Apan, A. and McDougall, K. (2013a), *Undertsanding the January 2011 Queensland Floods: the Role of Geographic Interdependency in Flood Risk Assessment for Urban Community and Infrastructures*, Brisbane, available at: http://anzdmc.com.au/

Espada, R., Apan, A. and McDougall, K. (2013b), *Using Spatial Modelling to Develop Flood Risk and Climate Adaptation Capacity Metrics for Vulnerability Assessments of Urban Community and Critical Water Supply Infrastructure*, International Society of City and Regional Planners (ISOCARP), Brisbane City.

Espada, R., Apan, A. and McDougall, K. (2013c), *Using Spatial Modelling to Develop Flood Risk and Climate Adaptation Capacity Metrics for Assessing the Vulnerability of Urban Community and Critical Electricity Infrastructure*, Modelling and Simulation Society of Australia and New Zealand (MSSANZ), Adelaide.

ESRI (2011), "ArcGIS resources", available at: http://resources.arcgis.com/en/help/main/10.1/index.html#//005p0000000n000000 (accessed February 2013).

Farrell, S., Hafner, S., Finley, M. and Robine, C. (2006), *New Jersey Beach Profile Network Annual Report on Shoreline Changes in New Jersey Coastal Reaches One Through Fifteen Raritan Bay to Delaware Bay Spring 2004 Through Fall of 2005*, The Richard Stockton College of New Jersey Coastal Research Center, NJ.

Feng, L.H. and Lu, J. (2010), "The practical research on flood forecasting based on artificial neural networks", *Expert Systems with Applications*, Vol. 37 No. 4, pp. 2974-2977.

Flegg, B. (2011), Transcript of Proceedings, *Queensland Floods Commission of Inquiry*, *Brisbane City*.

Gallopin, G. (2006), "Linkages between vulnerability, resilience, and adaptive capacity", *Global Environmental Change*, Vol. 16, pp. 293-303.

Gardner, M. and Dorling, S. (1998), "Artificial neural networks (the multilayer perceptron) – a review of applications in the atmospheric sciences", *Atmospheric Environment*, Vol. 32 Nos 14/15, pp. 2627-2636.

Geoscience Australia (2010a), "What is vulnerability?", available at: www.ga.gov.au (accessed 5 August 2011).

Geoscience Australia (2010b), "Flood basic: what is flood", available at: www.ga.gov.au/hazards/flood/flood-basics/what.html (accessed 30 June 2011).

Gosukonda, R., Mahapatra, A., Liu, X. and Kannan, G. (2015), "Application of artificial neural network to predict Escherichia coli 0157:H7 inactivation on beef surfaces", *Food Control*, Vol. 47, pp. 606-614.

Graupe, D. (2007), *Principles of Artificial Neural Networks*, 2nd ed., World Scientific Publishing Company, Singapore.

Gregoire, E. and Konieczny, S. (2006), "Logic-based approaches to information fusion", *Information Fusion*, Vol. 7 No. 1, pp. 4-18.

Hamaina, R., Leduc, T. and Moreau, G. (2012), "Towards urban fabrics characterization based on building footprints", in Gensel, J., Josselin, D. and Vandenbroucke, D. (Eds), *Bridging the Geographic Information Sciences, Lecture Notes in Geoinformation and Cartography*, Verlag Berlin Heidelberg, Springer.

Hannam, P. (2013), "Dam size isn't the problem, says researcher", available at: www.smh.com.au/environment/water-issues/dam-size-isnt-the-problem-says-researcher-20130228-2f7io.html (accessed 2014 February 2014).

Hinkel, J. (2011), "Indicators of vulnerability and adaptive capacity: towards a clarification of the science-policy interface", *Global Environmental Change*, Vol. 21 No. 1, pp. 198-208.

Hughey, E. and Bell, H. (2010), *Disaster Risk and Vulnerability*, Pacific Disaster Center, Hawaii.

IPCC (2001), *Climate Change 2001: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

Ipswich City Council (ICC) (2012), *Ipswich City Council Temporary Local Planning Instrument 01/2001*, Ipswich City Council, Ipswich City.

Jain, A., Mao, J. and Mohiuddin, K. (1996), "Artificial neural networks: a tutorial", *IEEE Computer*, pp. 31-44.

Jun, K.S., Chung, E.S., Kim, Y.G. and Kim, Y. (2013), "A fuzzy multi-criteria approach to flood risk vulnerability in south Korea by considering climate change impacts", *Expert Systems with Applications*, Vol. 40 No. 4, pp. 1003-1013.

Kalogirou, S., Florides, G.A., Pouloupatis, P.D., Christodoulides, P. and Joseph-Stylianou, J. (2015), "Artificial neural networks for the generation of a conductivity map of the ground", *Renewable Energy*, Vol. 77, pp. 400-407.

Linham, M.M. and Nicholls, R.J. (2010), "Flood hazard mapping", available at: http://climatetechwiki.org/content/flood-hazard-mapping (accessed 30 June 2011).

Lord Mayor's Taskforce on Suburban Flooding (2005), *Strategies to Reduce the Effect of Significant Rain Events on Areas of Brisbane Prone to Flooding*, Brisbane City Council, Brisbane City.

McMaster, R., Leitner, H. and Sheppard, E. (1997), "GIS-based environmental equity and risk assessment: methodological problems and prospects", *Cartography and Geographic Infomration Systems*, Vol. 24 No. 3, pp. 172-189.

Markopoulos, A.P., Manolakos, D.E. and Vaxevanidis, N.M. (2008), "Artificial neural network models for the prediction of surface roughness in electrical discharge machining", *Journal of Intelligent Manufacturing*, Vol. 19 No. 3, pp. 283-292.

Mele, P. and Crowley, D. (2008), "Application of self-organizing maps for assessing soil biological quality", *Agriculture, Ecosystems and Environment*, Vol. 126 Nos 3/4, pp. 139-152.

Middelmann, M. (2002), *Flood Risk in South East Queensland*, Institute of Engineers Australia, Melbourne.

Mirfenderesk, H. and Corkill, D. (2009), "The need for adaptive strategic planning: sustainable management of risk associated with climate change", *International Journal of Climate Change Strategies and Management*, Vol. 1 No. 2, pp. 146-159.

Mohanraj, M., Jayaraj, S. and Muraleedharan, C. (2015), "Applications of artificial neural networks for thermal analysis of heat exchangers – a review", *International Journal of Thermal Sciences*, Vol. 90, pp. 150-172.

Nasri, M. (2010), "Application of artificial neural networks (ANNs) in prediction models in risk management", *World Applied Sciences Journal*, Vol. 10 No. 12, pp. 1493-1500.

Ozkan, S.P. and Tarhan, C. (2016), "Detection of flood hazard in urban areas using GIS: Izmir case", *Procedia Technology*, Vol. 22, pp. 373-381.

Patwardhan, A., Downing, T., Leary, N. and Wilbanks, T. (2009), "Towards an integrated agenda for adaptation research: theory, practice and policy", *Current Opinion in Environmental Sustainability*, Vol. 1 No. 2, pp. 219-225.

Pavlin, G., de Oude, P., Maris, M., Nunnink, J. and Hood, T. (2010), "A multi-agent systems approach to distributed Bayesian infomration fusion", *Information Fusion*, Vol. 11 No. 3, pp. 267-282.

Pradhan, B. (2011), "GIScience Tools for climate change related natural hazards and modelling", in Joshi, P. and Singh, T. (Eds), *Geoinformatics for Climate Change Studies*, The Energy and Resources Institute, New Delhi.

Preston, B. and Stafford-Smith, M. (2009), "Framing vulnerability and adaptive capacity assessment: discussion paper", available at: www.csiro.au/org/ClimateAdaptationFlagship.html (accessed 22 October 2011).

Procesi, M., Buttinelli, M. and Pignone, M. (2015), "Geothermal favourability mapping by advanced geospatial overlay analyis: Tuscany case study (Italy)", *Energy*, Vol. 90 (Part 2), pp. 1377-1387.

QRA (2011), *Planning for Stronger, More Resilient Flood Plains*, City East Q, Queensland Reconstruction Authority.

Queensland Floods Commission of Inquiry (2011), *Queensland Floods Commission of Inquiry Interim Report*, Queensland Floods Commission of Inquiry, Brisbane City.

Queensland Floods Commission of Inquiry (QFCI) (2012), *Queensland Floods Commission of Inquiry Final Report*, Queensland Floods Commission of Inquiry, Brisbane City.

Queensland Museum (2011), "Brisbane Flood 2011", available at: www.southbank.qm.qld.gov.au/Events±and±Exhibitions/Exhibitions/2011/03/Brisbane±Floods±2011 (accessed 2 February 2012).

Queensland Reconstruction Authority (QRA) (2011), *Planning for Stonger, More Resilient Flood Plains Parts 1 and 2*, Queensland Reconstruction Authority, Brisbane City.

Raghuvanshi, T.K., Negassa, L. and Kala, P.M. (2015), "GIS based grid overlay method versus modeling approach – a comparative study for landslide hazard zonation (LHZ) in meta robi district of west Showa zone in Ethiopia", *The Egyptian Journal of Remote Sensing and Space Sciences*, Vol. 18 No. 2, pp. 235-250.

Reynolds, S. (2011), *Building Control for Flood Hazard Areas*, Queensland Flood Commission of Inquiry, Brisbane City.

Riad, P., Billib, M., Hassan, A., Salam, M. and El Din, M. (2011), "Application of the overlay weighted model and Boolean logic to determine the best locations for artificial recharge of groundwater", *Journal of Urban and Environmental Engineering*, Vol. 5 No. 2, pp. 57-66.

Robinson, A.A. (2011), *Opening Submission by Queensland Bulk Water Supply Authority Trading as Seqwater*, Queensland Flood Commission of Inquiry, Brisbane City.

Ruiz, M. and Hullermeier, E. (2012), "A formal and empirical analysis of the fuzzy gamma rank correlation coefficient", *Information Sciences*, Vol. 206, pp. 1-17.

Sadiq, R., Husain, T., Veitch, B. and Bose, N. (2004), "Risk-based decision-making for drilling waste discharges using a fuzzy synthetic evaluation technique", *Ocean Engineering*, Vol. 31 No. 16, pp. 1929-1953.

Sarkar, A. and Pandey, P. (2015), "River water quality modelling using artificial neural network technique", *Aquatic Procedia*, Vol. 4, pp. 1070-1077.

Shao-Hong, W., Tao, P. and Shan-Feng, H. (2012), "Climate change risk research: a case study on flood disaster risk in China", *Advances in Climate Change Research*, Vol. 3 No. 2, pp. 92-98.

Simmonds, J. (2011), *Statement of Jamie Simmonds*, Queensland Floods Commission of Inquiry, Brisbane City.

State of Queensland (SoQ) (2010), *'Increasing Queensland's Resilience to Inland Flooding in A Changing Climate: Final Report on Inland Flooding Study*, Department of Environment and Resource Management, Department of Infrastructure and Planning, and Local Government Association of Queensland, Brisbane City.

Sun, C. (2011), Transcript of Proceedings, *Queensland Floods Commission of Inquiry, Brisbane City*.

Szlafsztein, C. (2008), *Adaptation to Climate Change and Vulnerability Metrics: The Index of Usefulness of Practices for Adaptation (IUPA)*, Institute for Global Environmental Strategies, Tokyo.

Teasdale, G., Moran, B., Seda-Sanabria, Y. and Hunter, J. (2009), *Flood Modeling for the 2009 Dams Sector Exercise Series*, United States Society on Dams, Sacramento, CA.

The Mathworks, Inc (2013), *Neural Network Toolbox*, The Mathworks, Massachusetts.

Tompkins, E. and Adger, W.N. (2005), "Defining response capacity to enhance climate change policy", *Environmental Science and Policy*, Vol. 8 No. 6, pp. 562-571.

Torresan, S., Critto, A., Rizzi, J., Zabeo, A., Furlan, E. and Marcomini, A. (2016), "DESYCO: a decision support system for the regional risk assessment of climate change impacts in coastal zones", *Ocean and Coastal Management*, Vol. 120, pp. 49-63.

UNDP (1991), *Human Development Report*, Oxford University Press, New York, NY.

UNDP (1993), *Human Development Report*, Oxford University Press, New York, NY.

UNISDR (2009), *UNISDR Terminology on Disaster Risk Reduction*, United Nations International Strategy for Disaster Reduction, Geneva.

UNISDR and EUR-OPA (2011), *Climate Change Adaptation and Disaster Risk Reduction in Europe: A Review of Risk Governance*, United Nations International Strategy for Disaster Reduction (UNISDR) and Council of Europe (EUR-OPA), Geneva.

Valentina, G., Silvia, T., Andrea, C. and Antonio, M. (2014), "Multi-risk assessment: from natural hazards to climate change", *Geophysical Research Abstracts*, Vol. 16.

van den Honert, R.C. and McAneney, J. (2011), "The 2011 Brisbane floods: causes, impacts and implications", *Water*, Vol. 3 No. 4, pp. 1149-1173.

Vanneuville, W. Kellens, W. De Maeyer, P. Reniers, G. and Witlox, F. (2011), "Is 'flood risk management' identical to 'flood disaster management'?", available at: www.earthzine.org/2011/03/21/is-flood-risk-management-identical-to-flood-disaster-management/ (accessed 3 June 2011).

Walke, N., Reddy, G.O., Maji, A.K. and Thayalan, S. (2012), "GIS-based multicriteria overlay analysis in soil-suitability evaluation for cotton (gossypium spp.): a case study in the black soil region of central India", *Computers & Geosciences*, Vol. 41, pp. 108-118.

Westen, C.V. (2000), "Remote sensing for natural disaster management", *International Archives of Photogrammetry and Remote Sensing*, Vol. 33, pp. 1609-1617.

White, A. (2011), *Statement of Amanda White*, Queensland Floods Commission of Inquiry, Brisbane City.

Wong, D. and Lee, J. (2005), *Statistical Analysis of Geographic Information with ArcView GIS and ArcGIS*, John Wiley & Sons, Hoboken, NJ.

Wu, Y., Zhong, P.A., Xu, B., Zhu, F. and Ma, B. (2017), "Changing of flood risk due to climate and development in Huaihe River basin, China", *Stochastic Environmental Research Risk Assessment*, Vol. 31 No. 4, pp. 935-948.

Xing-peng, L., Ji-quan, Z., Wei-ying, C. and Zhi-jun, T. (2013), "Assessing maize drought for agricultural areas based on the fuzzy gamma model", *Journal of Integrative Agriculture*, Vol. 12 No. 3, pp. 532-540.

Yildiz, Z. and Uzun, H. (2015), "Prediction of gas storage capacities in metal organic frameworks using artificial neural network", *Microporous and Mesoporous Materials*, Vol. 208, pp. 50-54.

Zadeh, L. (1965), "Fussy sets", *Information and Control*, Vol. 8 No. 3, pp. 338-353.

Corresponding author
Rudolf Espada can be contacted at: Rudolf.Espada@usq.edu.au

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2. Zongmin Li, Xinxin Zhang, Yanfang Ma, Cuiying Feng, Asaf Hajiyev. 2019. A multi-criteria decision making method for urban flood resilience evaluation with hybrid uncertainties. *International Journal of Disaster Risk Reduction* **36**, 101140. [Crossref]
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4. Melissa Bedinger, Lindsay Beevers, Lila Collet, Annie Visser. 2019. Are We Doing 'Systems' Research? An Assessment of Methods for Climate Change Adaptation to Hydrohazards in a Complex World. *Sustainability* **11**:4, 1163. [Crossref]
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