

Flood Damage Assessment in Urban Areas

By

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DEDICATES TO MY PARENTS
FOR ALWAYS BEING MY INSPIRATION
WITH ENDLESS SUPPORT

ABSTRACT

Natural disaster prevention activities are attracting greater priority since prevention is more cost-effective and less uncertain than response, and aligned with the vision and mission of sustainable development. Increasing the resilience of communities and businesses is dependent on the extension of structural and non-structural risk mitigation activities. Hence, the nation-wide frameworks of natural disaster risk management are promoting a global movement from reactive activities (response and recovery) to proactive actions (prevention and mitigation). In Australia, flood risk management is of high priority since flood is a frequent natural hazard with significant financial consequences.

Flood risk assessment and flood damage estimation are the primary steps in the flood risk management process because they are essential for the identification and prioritisation of top priority areas, cost-benefit analysis, checking the feasibility of risk mitigation options, selecting best practices in risk reduction and land use planning. This research aims to develop a validated flood damage assessment framework for the geographical area of Australia using historical data collected in several disaster events to inform disaster management policy in support of the development of risk reduction measures.

In Australia, due to a lack of empirical data, most damage models are not calibrated with real damage data, and few studies have been conducted on the validation of results. In addition, most approaches are absolute, which is quite rigid and does not easily transfer across time and space. All approaches are of the traditional type, which relies on a deterministic relationship between type or use of the properties at risk and the depth of water. Thus, the interaction of most damage-influencing parameters and the uncertainty of data are neglected. This study has attempted to address these issues and the knowledge gaps.

Firstly, a comprehensive empirical data set including information on damage extent, flood impact variables and resistance factors was collected, and data mining, data preparation and data transformation were conducted. Since the function approach is a common and internationally accepted methodology for estimating the value of flood losses, some new relative multi-parameter flood damage assessment functions were derived, calibrated and validated for the most common residential and commercial building types in Australia. The functions were developed using the bootstrapping approach and considered the inherent uncertainty in the data sample. The performance of the new flood loss functions, in comparison to the empirical data, was contrasted with that of well-known flood damage assessment models from overseas and Australia. The new model was then transferred to a study area in Italy to check the ease of using local empirical data, evaluating the accuracy of the outcome, and assessing the ability to change parameters based on building practices across the world.

Flood damage assessment is a complicated process and can be dependent on a variety of parameters which are not considered in stage-damage functions. Accordingly, a tree-based model was developed for exploring the interaction, importance and influence of other damage-influencing parameters on the extent of losses. Finally, the candidate has explored the predictive performance of the new approaches (i.e. flood loss functions and tree-based flood loss models) in assessing the extent of physical damages after temporal and spatial transfer. The predictive power of these models was tested for precision, variation and reliability, and was also checked for some sub-classes of water depth and some groups of building type.

The advantages of the newly derived stage-damage functions compared to the existing Australian models include: calibration with empirical data, greater accuracy in results, a better level of transferability in time and space, consideration of the epistemic uncertainty of data, transparency of the logic behind the model and the ability to change parameters based on building practices across the world. Furthermore, results of the tree-based analysis showed that while water depth is the most significant damage predictor in the area of study, floor space, private precautionary measures, building value and building quality also correlate with the extent of flood losses. Also, the tree-

based models are shown to be more accurate than the stage-damage function. Thus, considering more parameters and taking advantage of tree-based models are recommended. Finally, it has been shown that considering more details of the damaging process can be useful for enhancing the level of transferability of damage models in time and/or space.

Overall, this thesis presents a significant contribution to the flood damage assessment process by offering a calibrated and validated flood loss estimation framework. The results provide the input data for subsequent damage reduction, vulnerability mitigation and disaster risk reduction.

DECLARATION

This is to certify that

- The thesis comprises of author's original work towards the degree of Doctor of Philosophy except where indicated;
- Due acknowledgement has been made in the text to all other material used;
- The thesis is fewer than 100,000 words in length, exclusive of references, tables, maps, bibliographies and appendices.

Roozbeh Hasanzadeh Nafari

Melbourne, January 2018

PREFACE

I hereby confirm the originality of this thesis based solely on the research work I conducted at the Department of Infrastructure Engineering, The University of Melbourne during my PhD candidature (July/2014 – January/2018). The chapters that have been published or submitted for publications in journals are listed in the “List of Publication”.

I was the main investigator of all journal papers and was responsible for all sections including concept formation, development of numerical models, data analysis of the acquired results, as well as the composition of the manuscripts. My PhD supervisors Professor Tuan Ngo and Professor Priyan Mendis have supervised my work and contributed to all the stages of the generated publications, the amount of contribution towards each publication are listed as below:

Author contribution: 70%	Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016. Calibration and validation of FLFArs – a new flood loss function for Australian residential structures. Nat. Hazards Earth Syst. Sci. 16, 15–27. [Chapter 3]
Author contribution: 70%	Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016. Development and evaluation of FLFAcs – A new Flood Loss Function for Australian commercial structures. Int. J. Disaster Risk Reduction. 17, 13-23. [Chapter 4]

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- Author contribution: 70% Hasanzadeh Nafari, R., Ngo, T., Mendis, P., 2016. An Assessment of the Effectiveness of Tree-Based Models for Multi-Variate Flood Damage Assessment in Australia. *Water* 8, 282. [Chapter 6]
- Author contribution: 70% Hasanzadeh Nafari, R. and Ngo, T., 2018. Predictive applications of Australian flood loss models after a temporal and spatial transfer, *Geomatics, Natural Hazards and Risk*, 9:1, 416-430. [Chapter 7]

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I also wish to sincerely thank the staff and postgraduate students from the Department of Infrastructure Engineering, especially my colleagues at the Centre for Disaster Management and Public Safety (CDMPS), for their friendship, generous assistance and unwavering support. Special thanks are also due to the staff, end-users, and colleagues at the Bushfire and Natural Hazards CRC (BNHCRC), who provided their valuable time, insights and feedback at different stages of this research project. Also, the financial contribution of the University of Melbourne, and the Commonwealth of Australia through the Cooperative Research Centre program is acknowledged.

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LIST OF PUBLICATIONS

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2. Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016. Development and evaluation of FLFAcs – A new Flood Loss Function for Australian commercial structures. *Int. J. Disaster Risk Reduction.* 17, 13-23. [Chapter 4]
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4. Hasanzadeh Nafari, R., Ngo, T., Mendis, P., 2016. An Assessment of the Effectiveness of Tree-Based Models for Multi-Variate Flood Damage Assessment in Australia. *Water* 8, 282. [Chapter 6]
5. Hasanzadeh Nafari, R. and Ngo, T., 2018. Predictive applications of Australian flood loss models after a temporal and spatial transfer, *Geomatics, Natural Hazards and Risk*, 9:1, 416-430. [Chapter 7]
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TABLE OF CONTENTS

1	INTRODUCTION.....	1
1.1	Motivation.....	1
1.2	Problem statement.....	3
1.3	Research scope.....	5
1.4	Research aims and objectives.....	5
1.5	Thesis outline.....	6
	References.....	10
2	LITERATURE REVIEW.....	13
2.1	Overview.....	13
2.2	Definitions.....	15
2.3	General procedure for flood damage assessment.....	20
2.3.1	Exposure and assets analysis.....	21
2.3.2	Classification.....	22
2.3.3	Damage-influencing parameters.....	23
2.3.4	Cost assessment.....	25
2.4	Economic Sectors.....	29
2.4.1	Residential sector.....	31
2.4.2	Commercial and industrial sector.....	35
2.5	Conclusions.....	39
	References.....	41
3	CALIBRATION AND VALIDATION OF FLFA_{rs}.....	46
3.1	Abstract.....	46
3.2	Introduction.....	47
3.3	Background.....	49
3.4	The Newly Derived Loss Model (FLFA _{rs}).....	51
3.5	Study Areas and Official Loss Data.....	54
3.5.1	Study Areas and Flood Events.....	54
3.5.2	Official Flood Loss Data.....	60
3.6	Derivation and Calibration of FLFA _{rs} with the Flood Loss Data of 2013.....	65
3.7	Models Comparison.....	69

3.7.1	Applied Damage Models.....	69
3.7.2	Results Comparison and Model Validation for the Maranoa Study Area.....	72
3.8	Conclusions.....	75
	Acknowledgements.....	76
	References.....	77
4	DEVELOPMENT AND EVALUATION OF FLFA_{CS}.....	83
4.1	Abstract.....	83
4.2	Introduction.....	84
4.3	Background.....	86
4.4	The newly derived function (FLFA _{CS}).....	89
4.5	Study areas and official data.....	91
4.5.1	Study areas and flood events.....	91
4.5.2	Official flood data set.....	96
4.6	Derivation and calibration of the new model.....	97
4.7	Models comparison.....	100
4.7.1	Applied damage models.....	100
4.7.2	Results comparison and model validation.....	103
4.8	Conclusions.....	109
	Acknowledgements.....	110
	References.....	111
5	FLOOD LOSS MODELLING WITH FLF-IT.....	118
5.1	Abstract.....	118
5.2	Introduction.....	119
5.3	Case study.....	122
5.3.1	Event description.....	122
5.3.2	Data description.....	123
5.4	The FLFA method.....	126
5.5	Calibration of FLF-IT.....	127
5.6	Model validation.....	129
5.6.1	Applied damage models.....	129
5.6.2	Result comparison and model validation.....	130
5.7	Conclusions.....	137
	Acknowledgment.....	139
	References.....	140

6	AN ASSESSMENT OF THE EFFECTIVENESS OF TREE-BASED MODELS.....	148
6.1	Abstract	148
6.2	Introduction	149
6.3	Study Area and Data	152
6.4	Statistical Methods	162
6.4.1	Regression Trees	162
6.4.2	Bagging Decision Trees	164
6.4.3	Comparing the Performance of the Tree-Based Models with FLFArs	164
6.5	Results and Discussion.....	165
6.5.1	Importance and Interaction of the Damage Influencing Parameters	165
6.6	Conclusions	171
	Acknowledgements:.....	173
	References.....	174
7	PREDICTIVE APPLICATIONS OF AUSTRALIAN FLOOD LOSS MODELS AFTER A TEMPORAL AND SPATIAL TRANSFER.....	180
7.1	Abstract	180
7.2	Introduction	181
7.3	Flood Events and Damage Data	184
7.3.1	Study Area and Flood Event in 2013	184
7.3.2	Study Area and Flood Event in 2012	185
7.3.3	Empirical Damage Data Collection.....	186
7.4	Damage Models.....	187
7.4.1	FLFArs	187
7.4.2	Regression Trees	190
7.5	Validation of the models	193
7.6	Results and Discussion.....	195
7.7	Conclusions	199
	Acknowledgements.....	201
	References.....	202
8	CONCLUSIONS.....	208
8.1	Overview	208
8.2	Conclusions	210
8.3	Recommendations for Future Work	213
9	APPENDIX: PUBLICATIONS	215

LIST OF FIGURES

Figure 1-1: Flood risk management activities.....	2
Figure 1-2: The process of flood risk prevention.....	3
Figure 1-3: Thesis structure.....	9
Figure 2-1: Cost of Natural Disasters in Australia (Bureau of Transport Economics, 2001)	14
Figure 2-2: Flood Risk Assessment and Management Framework.....	15
Figure 2-3: Flood impacts process	16
Figure 2-4: Flood damage assessment spatial scale	18
Figure 2-5: General procedure for flood damage assessment	20
Figure 2-6: Visualisation of a relative stage-damage function.....	26
Figure 2-7: FLEMOps model for the estimation of residential building structures flood losses	32
Figure 2-8: USACE model for the estimation of residential building structures flood losses	33
Figure 2-9: GA model for the estimation of residential building structures flood losses	34
Figure 2-10: FLEMOcs model for the estimation of commercial building structures flood losses	37
Figure 3-1: Map of Bundaberg Regional Council.....	55
Figure 3-2: Bundaberg ground elevation.....	55
Figure 3-3: Burnett River catchment map.....	56
Figure 3-4: Inundation map of 2013 flood.....	57
Figure 3-5: Map of Maranoa Regional Council	58
Figure 3-6: Basin-level flood modelling for Bungil Creek.....	59
Figure 3-7: Boundary of the 2012 historic flood event.....	60
Figure 3-8: Empirical data points collected from 2013 Bundaberg flood event and utilised for calibrating FLFArs	63
Figure 3-9: Illustration of condition rating and sub-assembly loss vs overall building loss for one-storey buildings with timber walls	64
Figure 3-10: Visualization of minimum, most-likely and maximum damage functions, calculated by bootstrap and chi-square test, for one-storey buildings with timber wall	68
Figure 3-11: Visualization of minimum, most-likely and maximum damage functions, calculated by bootstrap and chi-square test, for two-storey buildings with brick wall	68
Figure 3-12: Model comparison for one-storey buildings.....	71
Figure 3-13: Model comparisons for two-storey buildings.....	71
Figure 3-14: Residual plot used for comparing the performance of selected damage functions relative to empirical loss ratios.....	75
Figure 4-1: Map of Bundaberg City	93
Figure 4-2: Bundaberg ground elevation.....	93
Figure 4-3: Burnett River catchment map.....	94
Figure 4-4: Inundation map of 2013 flood.....	95
Figure 4-5: Visualisation of minimum, most-likely and maximum damage functions, calculated by bootstrap and chi-square test goodness of fit	100

Figure 4-6: Comparison among applied damage functions from overseas	103
Figure 4-7: Residual plot used for comparing performance of the selected damage functions relative to the empirical loss ratios.....	109
Figure 5-1: Identification of case study, flooding from the river Secchia during January 2014 in central Emilia-Romagna, northern Italy	123
Figure 5-2: Visualisation of the empirical damage records suffered by the individual dwellings during the flood event of 2014	125
Figure 5-3: Empirical data utilised to calibrate the FLF-IT model	126
Figure 5-4: Visualisation of minimum, most likely and maximum damage functions, calculated by bootstrap and chi-square test of goodness of fit	129
Figure 5-5: Comparison of the flood damage estimation models' precision per water-depth class	133
Figure 5-6: Comparison of the flood damage estimation models' precision per water-depth class	134
Figure 5-7: Visualisation of the workflow and the methodological steps of the study	137
Figure 6-1: Map of Bundaberg Regional Council.....	154
Figure 6-2: Bundaberg ground elevation.....	154
Figure 6-3: A part of the Burnett River catchment related to the area of the study	155
Figure 6-4: Inundation map of 2013 flood	156
Figure 6-5: Map of Maranoa Regional Council	157
Figure 6-6: Boundary of the 2012 historic flood event	157
Figure 6-7: Scatter plot showing the relation between loss ratio and water depth	162
Figure 6-8: Comparison of various pruned regression-trees, based on the mean absolute error (MAE) calculated by a 10-fold cross-validation technique.....	166
Figure 6-9: Regression tree with 19 leaves for estimating the structural loss ratios	166
Figure 6-10: Out-of-bag feature importance for bagging decision trees	169
Figure 6-11: Comparison of the flood damage estimation models	171
Figure 7-1: Topographic map of Bundaberg	185
Figure 7-2: Flood inundation boundary in the area of the study after the 2012 inundation event	186
Figure 7-3: Minimum, most likely and maximum FLFArs stage-damage functions for one-storey buildings with timber walls	188
Figure 7-4: Minimum, most likely and maximum FLFArs stage-damage functions for two-storey buildings with timber walls	189
Figure 7-5: Minimum, most likely and maximum FLFArs stage-damage functions for one-storey buildings with brick walls	189
Figure 7-6: Minimum, most likely and maximum FLFArs stage-damage functions for two-storey buildings with brick walls	190
Figure 7-7: Pruned tree (RTp) with 12 leaves	192
Figure 7-8: Unpruned tree (RTup) with 21 leaves	193
Figure 7-9: Comparison of the models' precision per water-depth class.....	197
Figure 7-10: Comparison of the models' precision per building type.....	198

LIST OF TABLES

Table 2-1: Different types of flood damages.....	17
Table 2-2: Damage-influencing parameters including flood impacts and resistance factors.....	25
Table 2-3: Advantages and disadvantages of empirical and synthetic models	28
Table 2-4: Advantages and disadvantages of relative and absolute models	28
Table 2-5: Summary of the aspects of flood loss estimation	30
Table 2-6: Comparison of four flood damage models for residential sector.....	34
Table 2-7: Average potential damage for large commercial buildings	36
Table 2-8: Comparison of three flood damage models for the commercial sector	38
Table 3-1: sub-Assembly replacement values for the common types of residential buildings as a percentage of the total building replacement value.....	62
Table 3-2: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test for one-storey buildings	67
Table 3-3: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test for two-storey buildings	67
Table 3-4: Comparison of different loss estimates with the observed flood damage on residential building structures for the flood event of February 2012.....	73
Table 3-5: Numerical comparison and error statistics of depth-damage function performance for the flood event of February 2012	74
Table 4-1: Sub-assembly replacement values for the common types of commercial buildings as a percentage of the total building replacement value	97
Table 4-2: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test goodness of fit.....	99
Table 4-3: Numerical comparison and error estimation for performance of the applied damage functions.....	107
Table 4-4: Comparison of mean loss ratios estimated by the applied damage models with the resampled loss data	108
Table 5-1: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test of goodness of fit.....	128
Table 5-2: Error estimation for the performance of the FLF-IT model	131
Table 5-3: Comparison of total absolute losses estimated by FLF-IT with the 95% confidence interval of the resampled damage records.....	135
Table 6-1: Description of the 13 candidate predictors	161
Table 6-2: Pearson correlation of the 13 final candidate predictors and loss ratio	161
Table 6-3: Damage-influencing variables of regression tree with 19 leaves	167
Table 7-1: Explanation of the examined predictors considered for data mining	191
Table 7-2: Model evaluation criteria.....	195
Table 7-3: Comparison of the models' predictive capacity for the flood event of February 2012	196

1 INTRODUCTION

1.1 Motivation

When a disaster occurs in densely populated urban areas, the damage bill is high, and the population displacement is considerable. To cope with these challenges and grow sustainably, urban developments should be planned based on a good understanding of disaster risks. Understanding disaster risk is the primary step of natural peril event management frameworks (e.g. the Sendai framework for Disaster Risk Reduction) because it is essential for prioritisation of disaster risk mitigation projects, cost-benefit analysis, checking the feasibility of risk mitigation options, selecting best practices in risk reduction and land use planning. In this regard, since risk is defined as the probability and magnitude of expected damages, the estimation of negative consequences and the assessment of probable damages could be considered as the core element of understanding disaster risk (Emanuelsson et al., 2014).

Probability * Negative Consequences = Risk

Flood is the most expensive natural disaster in Australia and the world, and due to urban consolidation (i.e. growth in the value and vulnerability of the exposed assets) and climate change, flood risk has been increasing considerably (Hasanzadeh Nafari et al., 2016a). Flood risk management activities can be categorised as prevention, response and recovery groups (Fig. 1-1).

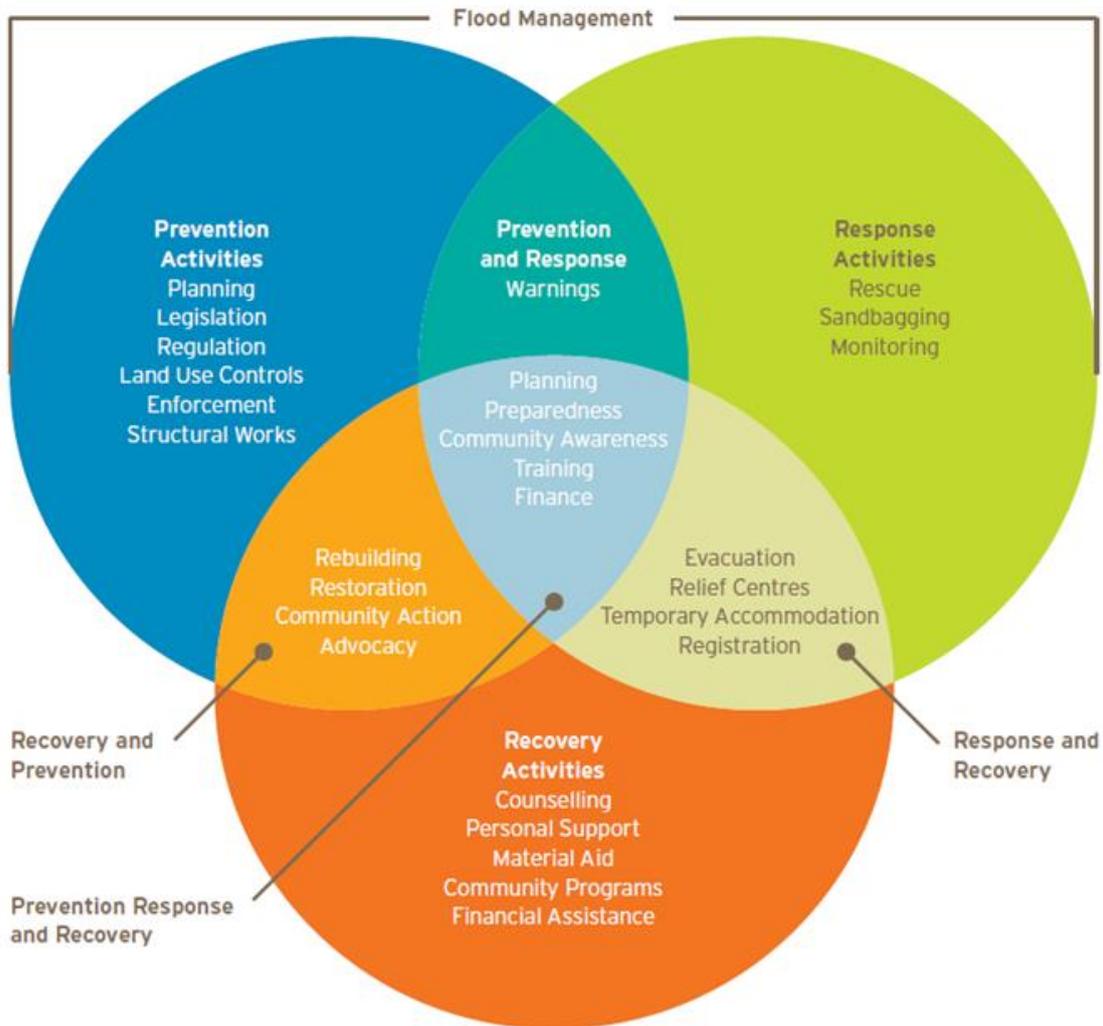


Figure 1-1: Flood risk management activities

The international frameworks of natural peril event management are promoting a global movement from disaster management to disaster reduction (i.e. being more proactive rather than reactive). Accordingly, prevention activities are attracting further attention since they are more cost-effective, less uncertain, and entirely aligned with the vision and mission of sustainable development. In this regard, as stated earlier, understanding flood risk (i.e. flood mapping and assessing flood risk) could be considered as the primary step of the flood risk prevention framework (Fig. 1-2).

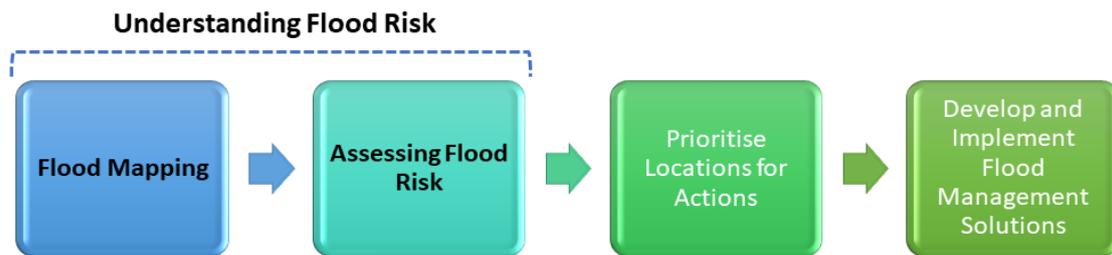


Figure 1-2: The process of flood risk prevention

Overall, flood is known to be the costliest natural disaster, necessitating greater attention to flood risk management. Flood risk prevention activities are of higher priority than response and recovery issues. Understanding flood risk, including flood mapping and flood risk assessment, is the primary step in the flood risk prevention process. While much effort has gone into flood mapping, flood risk assessment models are still subject to a high level of uncertainty (Kreibich and Thieken, 2008; Merz et al., 2004; Meyer et al., 2013). In this regard, flood damage estimation is an important component of flood risk assessment, and inaccurate damage estimation leads to wasted effort, money and resources for the organisations involved in flood risk mitigation (Hasanzadeh Nafari et al., 2016b; Merz et al., 2010).

1.2 Problem statement

Flood is a frequent natural hazard that has significant financial consequences for Australia, i.e. 29% of the total cost for the nation's economy and the built environment (Bureau of Transport Economics, 2001). Although the emergency response is very successful in Australia in terms of saving human lives, preparedness for natural disaster impacts with reference to loss reduction and damage mitigation has been less successful. It should also be noted that the value of exposed properties has been increasing exponentially, thereby raising sensitivity in the financial sectors.

To be more precise, the existing Australian approaches to flood risk assessment are of the traditional type, which relies only on a deterministic relationship between the type

or use of properties at risk, and the depth of water. In these methods, the variability of the real world and the uncertainty of the data have been neglected. In addition, the interaction and significance of most damage-influencing parameters are not taken into account. Hence, the outcomes are uncertain, and the performance is inaccurate. In addition, due to a lack of historical data, most Australian flood loss estimation models are not calibrated with actual damage data. Model calibration is an important factor for the accuracy of the outcome, especially when the water depth is the only hydraulic parameter taken into account (Cammerer et al., 2013; Chang et al., 2008; McBean et al., 1986). Furthermore, few studies have also been conducted on the validation of Australian models. Model validation, in contrast to hydraulic inputs and flood information, has a more significant contribution to the preciseness of the performance for damage prediction, particularly when the model has been transferred in time and/or space (Apel et al., 2009; de Moel and Aerts, 2011; Merz et al., 2010; Meyer et al., 2013).

Another important parameter which affects the flexibility and precision of a model is the type of the damage model. Most existing Australian models are the absolute type, which is more rigid for transfer in time and space. For instance, the RAM report (Sturges and Associates, 2000) claims that the outcomes of the ANUFLOOD approach (Smith, 1994), as one of the most commonly used Australian absolute models, should be increased by 60% since the model was prepared based on the empirical data collected in 1986. Furthermore, it is not recalibrated regularly based on the variation of market values and the inflation in costs of assets. Variation in the values of assets due to regional differences (i.e. the price of raw materials and wages) also reduces the flexibility and transferability of the absolute type flood damage models for use in a new study area (Merz et al., 2010).

To cope with these challenges and to resolve these issues requires transparency and access to the logic behind the methods. In other words, to enhance the methods' transferability, recalibrate the models regularly, validate the performances, or modify the parameters, the logic behind the approaches should be clear enough for the end users

and researchers. However, in this regard, a general lack of information is observed, and most approaches are published based only on a generic report (Hasanzadeh Nafari et al., 2016b). Accordingly, the logic of these models is not transparent enough to access or understand, and the models are not flexible enough to generalise to other types of building or flood.

1.3 Research scope

The focus of this study is on the monetary cost of physical damage to urban buildings due to a short duration of riverine inundation. The spatial extent of damage estimation processes is micro-scale, and the target economic sectors are residential and commercial building structures.

1.4 Research aims and objectives

This research aims to develop a validated flood damage assessment framework for the geographical conditions (building specification and flood characteristics) of Australia using historical data collected from recent extreme events to inform disaster management policy in support of the development of risk reduction measures. A comprehensive flood damage model based on the local conditions of Australia can promote the assessment of economic impacts of an extreme flood event in the future, and the results will provide decision-makers with an essential tool for planning better risk mitigation strategies and actively responding to flood disasters. The specific objectives of this research are listed as follows:

- To develop, calibrate, and validate some novel flexible multi-parameter flood damage assessment functions, considering the inherent uncertainty in the data sample, and the probabilistic relationship between the vulnerability features of the properties at risk and the depth of water.
- To transfer the newly derived model to a study area overseas by checking the simplicity of utilising local empirical data, evaluating the accuracy of the outcome,

Chapter 1: Introduction

and assessing the ability to change parameters based on building practices across the world.

- To establish a tree-based model for predicting the magnitude of damage and exploring the interaction, importance, and influence of different damage-influencing parameters on the extent of losses.
- To evaluate and compare the predictive capability and the reliability of the newly derived flood loss estimation models after a temporal and spatial transfer.

1.5 Thesis outline

The outline of this thesis is described as follows:

Chapter 2: Literature review

A comprehensive literature review is conducted on the background of flood damage assessment, which describes the importance of damage assessment, the related definitions, the procedure of loss estimation (exposure analysis, exposure classification, influencing parameters and cost assessment), the focus of this study, and the related studies previously performed in this research area. Finally, the knowledge gaps in Australian models are discussed, which are addressed in this research.

Chapter 3: Calibration and validation of FLFA_{rs} - a new flood loss function for Australian residential structures

The function approach or flood loss function is an internationally accepted standard for the estimation of flood damages in urban areas. In addition, a considerable portion of urban flooding losses is allocated to the residential and commercial sectors. Accordingly, this part of the study has attempted to generate some novel multi-parameter stage-damage functions for the common types of residential buildings in Australia. The functions are of the relative type and are calibrated and validated with

Chapter 1: Introduction

flood damage data collected in several disaster events. The advantages of this approach include a better level of transferability in time and space, the ability to utilise empirical data, the facility to change parameters based on building practices (different foundation height, ground elevation, percent of damages below ground, number of storeys, height of storeys, maximum damage as a percentage and the beginning elevation for damage) across the world, and the accuracy of the outcomes. Additionally, the study has illustrated a bootstrapping approach to the empirical data to consider the epistemic uncertainty of the data set and to assist in describing confidence limits around the flood loss function parameters.

Chapter 4: Development and evaluation of FLFA_{cs} - a new flood loss function for Australian commercial structures

Having carried out the work for the residential sector, this study focuses on the development of a new multi-parameter stage-damage function for the commercial sector. Flood losses to commercial buildings affect the Australian economy considerably, and a significant portion of urban flood losses is usually dedicated to this sector. However, there are not many models for the estimation of flood damage to commercial buildings, and their results are not reliably accurate. Thus, there is an urgent need for a project to derive a new stage-damage function for Australian commercial properties. The newly derived flood loss function has all the advantages of the approach presented for residential properties and has been developed for the most common type of commercial buildings in Australia.

Chapter 5: Flood loss modelling with FLF-IT: a new flood loss function for Italian residential structures

In this chapter, the newly derived stage-damage function has been transferred to a study area in Italy to modify the model parameters based on local empirical data and building practices across the world. Accordingly, the model has been modified based on

empirical damage data collected from a recent flood event and a representative group of residential buildings in Italy. The performance of the newly derived model has been validated, and its predictive capacity has also been contrasted with other damage models frequently used in Europe.

Chapter 6: An assessment of the effectiveness of tree-based models for multi-variate flood damage assessment in Australia

Flood damage is a complicated process, which might be dependent on a variety of parameters that are neglected in stage-damage functions. Accordingly, this part of the study has attempted to investigate and explore the interaction and significance of more damage-influencing parameters such as flow velocity, water contamination, precautionary measures, emergency measures, flood experience, floor area, building value, building quality and socioeconomic status. The study has used tree-based models and a historical dataset which includes information on damage extent, flood impact variables and resistance factors. Tree-based models are frequently used in the hydrology domain. However, this approach is relatively new in flood-loss modelling, and it has not been used for Australia. The newly derived models are calibrated using empirical data, and their performances are validated for predicting the extent of losses in flood events with the same geographical conditions (i.e. flood characteristics and building specifications) as the area of study.

Chapter 7: Predictive applications of Australian flood loss models after a temporal and spatial transfer

In this final part of this research, the authors have investigated the predictive capacity of the new flood loss models (i.e. flood loss functions and tree-based models) in assessing the extent of physical damages after a temporal and spatial transfer. The predictive power of these models is tested for precision, variation and reliability. The prediction capacity is also checked for some sub-classes of water depth and some

groups of building types. It has been shown that considering more details of the flood damage process can improve the transferability of damage prediction models.

Chapter 8: Conclusions and recommendations

The chapter summarises the major findings of this research and proposes potential study areas for future researchers.

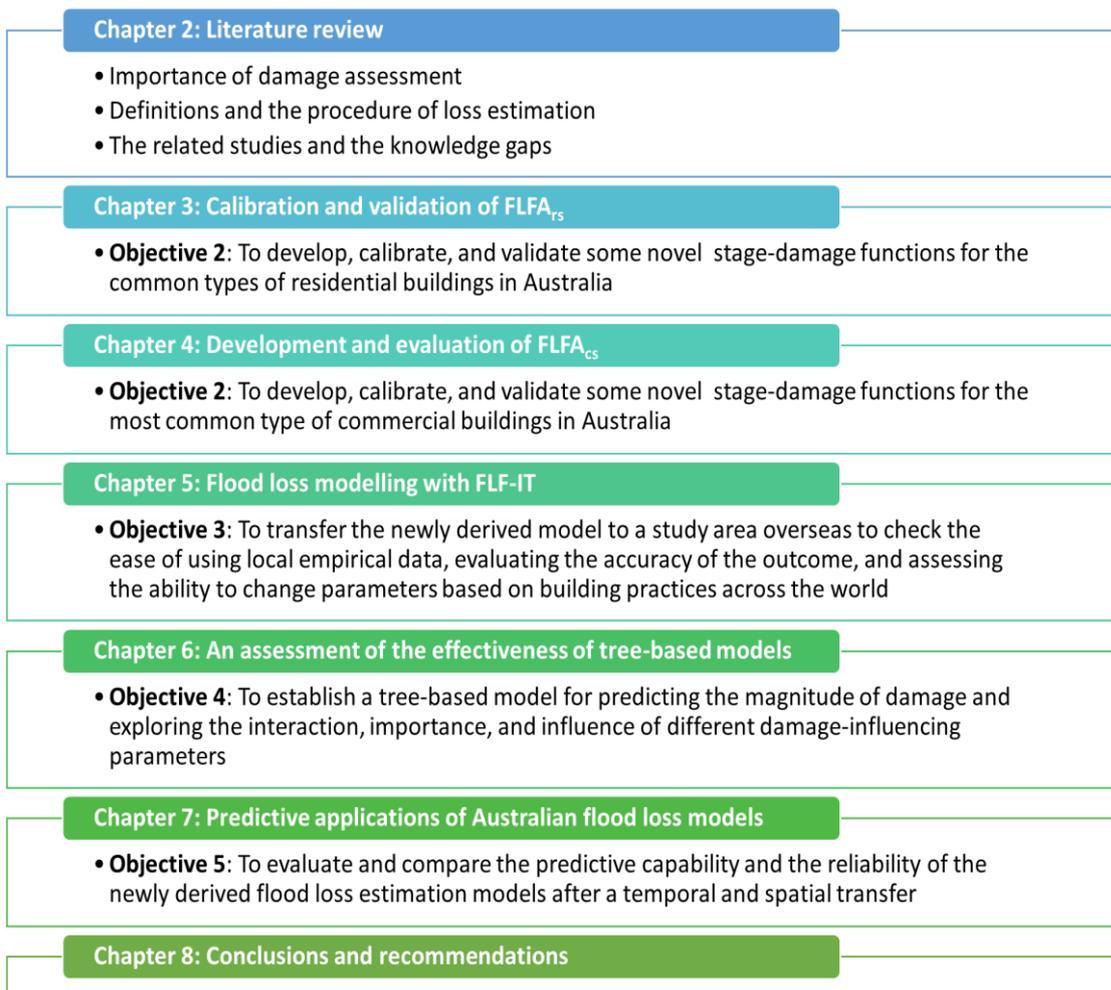


Figure 1-3: Thesis structure

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Chapter 1: Introduction

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2 LITERATURE REVIEW

2.1 Overview

Risk is defined as the probability and magnitude of expected damages as a result of hazard, exposure and vulnerability. Thus, damage estimation is the core element of risk assessment, and its outcome is substantial for decision-makers dealing with risk management, who need to prioritise risk mitigation options and choose the best practices. Loss reduction is one of the crucial concerns of decision makers, urban planners, insurance companies and engineers in terms of seeking to decrease the probability of risk from disasters.

Flood is known to be the costliest natural disaster in Australia and the world (Fig. 2-1). In recent decades, the extent of flood losses has increased due to climate change and urban consolidation, necessitating greater attention to flood risk management. While much effort has gone into emergency management and flood mapping, flood damage models are still crude, and understanding of the damage process is highly limited.

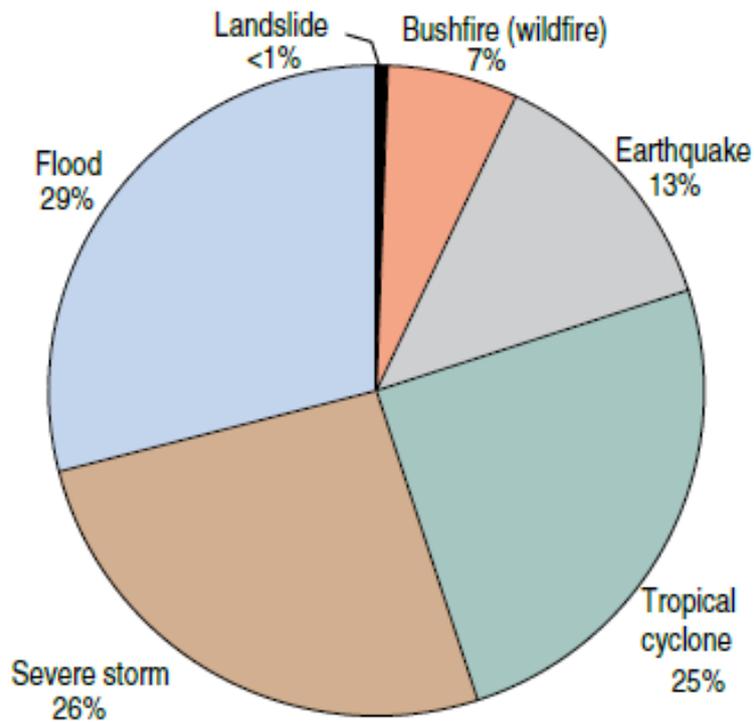


Figure 2-1: Cost of Natural Disasters in Australia (Bureau of Transport Economics, 2001)

Flood damage estimation is an indispensable part of flood risk management, which is required for vulnerability assessment, risk map preparation, top priority locations identification, the optimal decision on mitigation options and financial appraisals fulfilment (Fig. 2-2) (Merz et al., 2010). Accordingly, flood impact assessment methods need to be more carefully considered to protect the population against the impacts of future flood scenarios, increase the resilience of communities and businesses, and decrease the probability of losses in a systematic way.

damage (e.g. damage to properties and building contents) occurs due to the physical contact between floodwater and flooded objects during a flood event. Indirect damages (e.g. disruption of supply chain or public transport outside the flooded regions) are the induced effect of the direct losses, and they may happen outside of the flood boundary or after inundation (Fig. 2-3). Thus, it is obvious that the identification and quantification of indirect losses is a complicated process. In this context, tangible losses (e.g. damage to infrastructure and agriculture plants) can be expressed in monetary terms, while the extent of intangible groups (e.g. loss of life and injuries) cannot (see Table 2-1) (Hasanzadeh Nafari et al., 2016a).

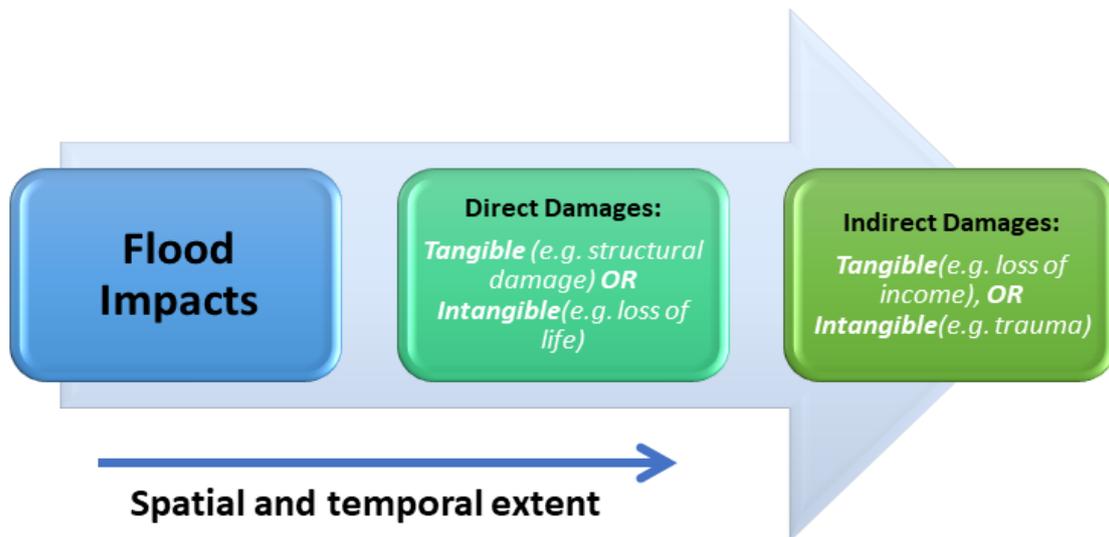


Figure 2-3: Flood impacts process (Hasanzadeh Nafari et al., 2013)

Table 2-1: Different types of flood damages (Molinari, 2011)

Exposed object		Damage	Type
Economic	Residential buildings	Structural damage, e.g. building fabrics	Direct, tangible
		Contents damage, e.g. furniture	Direct, tangible
		Additional cost, i.e. clean up	Indirect, tangible
		Protective measures, e.g. sandbag	Indirect, tangible
		Sentimental loss, i.e. loss of memorabilia	Indirect, intangible
	Commercial/industrial buildings	Structural damage, e.g. building fabrics	Direct, tangible
		Contents damage, e.g. products and stock	Direct, tangible
		Additional cost, i.e. production interruption	Indirect, tangible
		Protective measures, e.g. bund walls	Indirect, tangible
	Lifeline and infrastructures	Structural damage, e.g. building fabrics	Direct, tangible
		Additional cost, i.e. supply chain disruption	Indirect, tangible
		Additional cost, i.e. service disruption	Indirect, intangible
	Public/service buildings	Structural damage, e.g. building fabrics	Direct, tangible
		Contents damage, e.g. movable inventories	Direct, tangible
		Additional cost, i.e. service disruption	Indirect, tangible
		Protective measures, e.g. bund wall	Indirect, tangible
		Sentimental loss, i.e. loss of memorabilia	Indirect, intangible
	Social	Population	Physical, e.g. life loss and injury
Psychological, e.g. trauma			Indirect, intangible
Environmental	Agriculture plants and nature	Physical loss, e.g. crop	Direct, tangible
		Additional cost, i.e. loss of income	Indirect, tangible
		Additional cost, i.e. supply chain disruption	Indirect, tangible
		Protective measures, e.g. sandbag	Indirect, tangible
		Additional cost, i.e. service disruption	Indirect, intangible
		Ecological damage and environmental goods	Direct, intangible
		Sentimental loss	Indirect, intangible

Damages could be assessed or expressed as actual or potential. Potential damage means the maximum possible costs of flooding in the absence of any mitigation measures. Actual loss is the magnitude of real damages for a specific flood scenario and in the presence of real reduction actions (Gissing and Blong, 2004; Smith, 1994).

The spatial scale of damage estimation processes may vary from micro- to meso- or macro-scales (see Fig. 2-4). The focus of damage assessment models with the micro-

scale unit is on individual flooded objects or elements at risk, e.g. roads, buildings or bridges. However, by changing the spatial scale of models to the meso- or macro-scale, the spatial extent would be increased to land use units (e.g. commercial or residential zones and zip code areas) or large area regions (e.g. municipalities) (André et al., 2013; Jongman et al., 2012b).

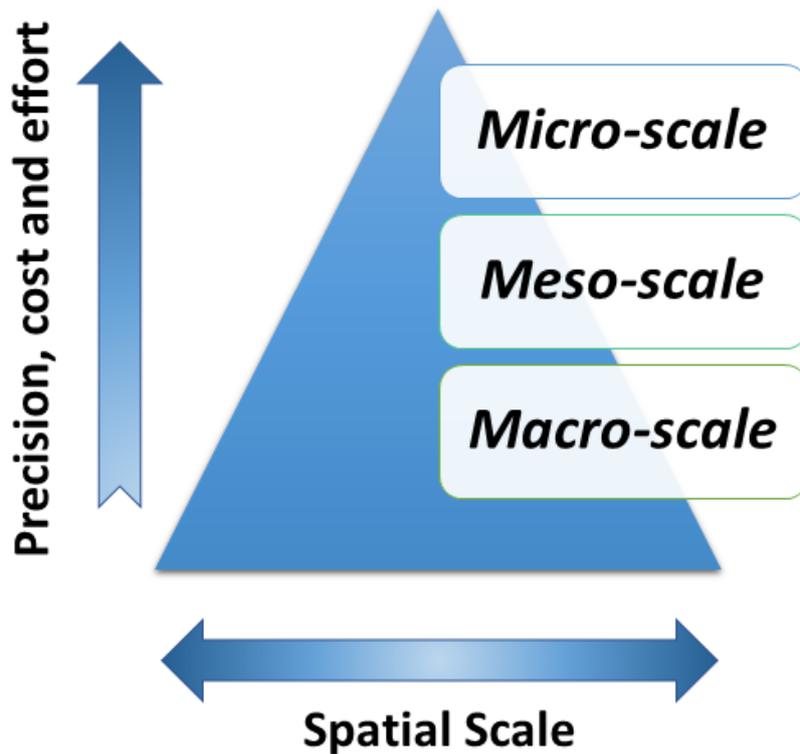


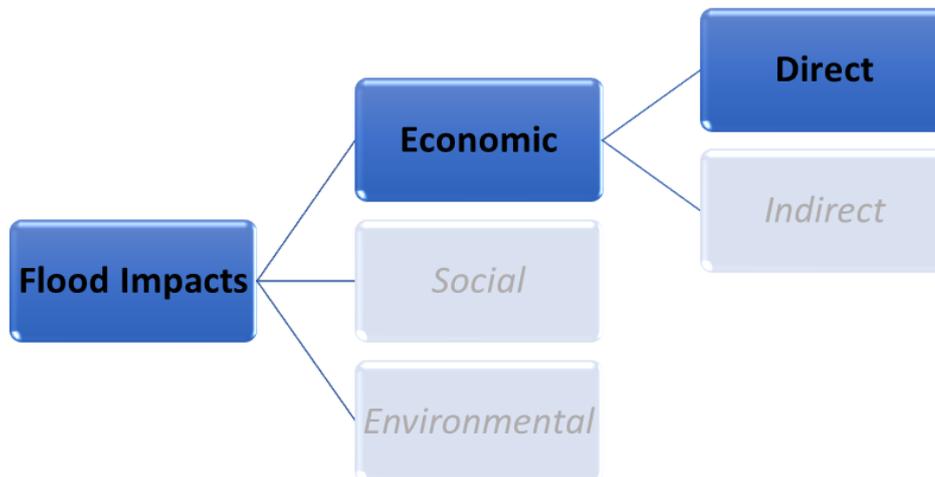
Figure 2-4: Flood damage assessment spatial scale

The economic evaluation may be carried out based on the replacement cost or the depreciated value (i.e. the actual value at the time of inundation) of damaged components. Damage assessment based on the full replacement cost of old goods may lead to the overestimation of losses, while replacement could be cheaper than repair if the extent of damage is great or the damaged components are out of production (Hasanzadeh Nafari et al., 2016b; Merz et al., 2010).

Finally, based on the timing of the study, flood damage assessments are categorised into two main groups, namely ex-ante and ex-post. Ex-ante damage assessment is the estimation of the potential losses before the event. Ex-post damage assessment aims at coordination of response and recovery issues, and the assessment of costs after an event. Ex-post damage assessment results can also be used for the calibration of ex-ante damage assessment models (André et al., 2013).

The rationale of damage assessment models, the boundary of inundation, the spatial scale of methods, the timing of the study, and the logic behind the study are dependent on the purposes of use and the sector of end-users. For instance, while insurance and reinsurance companies need to perform their appraisal based on their responsibilities, services and agreements; policy decision-makers may do this based on other concerns such as prioritisation of locations or selection of a set of risk mitigation options (Merz et al., 2010).

- **The focus of this study is on ex-ante direct, tangible damages of the flood.**



2.3 General procedure for flood damage assessment

Flood damage assessment can be fulfilled in the following steps (Hasanzadeh Nafari et al., 2013) (see Fig. 2-5):

- Exposure analysis: assessing the number, dimension, and value of people and goods in a dangerous area using inundation and land-use maps;
- Classification: categorising the flooded objects into homogeneous sectors or classes based on the type of use;
- Damage-influencing parameters: evaluation the flood impact factors and vulnerability features for every class of exposure;
- Cost assessment: making a relationship among the vulnerability factors, the impact parameters and the extent of losses for each category at risk.

All steps of the general procedure are explained in more detail based on the focus of this study hereafter.

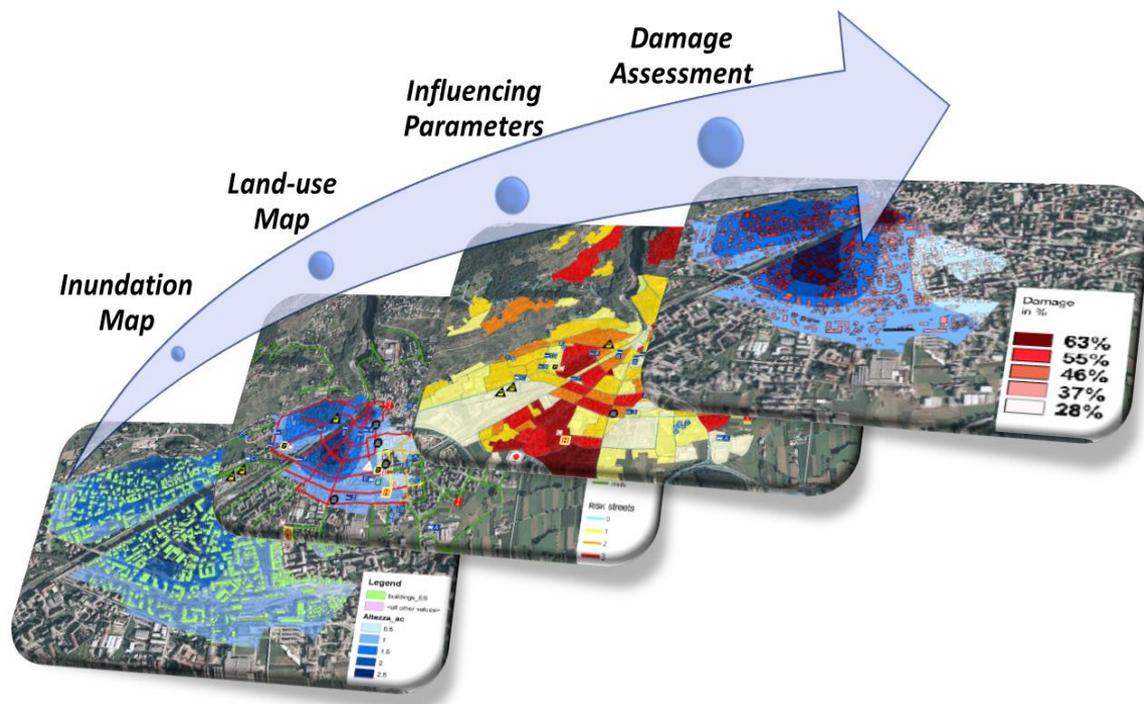


Figure 2-5: General procedure for flood damage assessment

2.3.1 Exposure and assets analysis

The exposure value is a function of time and space. Through time, the value of elements at risk may be subject to a variation due to inflation, renovation or age. On the other hand, the values of assets differ according to regional factors, e.g. price of raw materials and wages. Thus, the availability of an updated local dataset has a significant relationship with the accuracy of exposure analysis. Furthermore, exposure assessment as a result of an overlap between land-use data and inundation map can be carried out at the micro-, meso-, or macro-scales depending on the availability of data, the required accuracy and the aim of analysis (Merz et al., 2010).

In Australia, the construction (replacement) costs proposed by Blong (2003) and the National Exposure Information System of Australia (2014) are the most commonly used model and dataset for exposure analysis (Blong, 2003; Dunford et al., 2014). The Blong (2003) micro-scale model represents the replacement cost of all building types per square metre. In this model, the replacement cost of a medium-sized residential building has been considered as the unit of assessment, and the construction costs of other buildings are compared with this unit. Accordingly, the variation in building type and the floor area are adjusted using the cost and replacement ratios (Blong, 2003).

Geoscience Australia (GA) undertook the development of the National Exposure Information System (NEXIS) at the SA1 (Statistical Area Level 1) spatial scale. NEXIS is a comprehensive meso-scale dataset which aims to capture all exposure information of residential, commercial and industrial buildings across Australia. The dataset includes information about (Dunford et al., 2014):

- People: population estimate based on the Australian Bureau of Statistics (ABS) 2011, residents' income, ownership status, age, level of education and other socioeconomic factors;
- Buildings: sectors or economic activities, type of building, construction type (e.g. wall and roof materials), number of storeys, age, areas, replacement cost of structures and its contents, and other parameters that contribute to how a building resists impacts.

2.3.2 Classification

Damage assessment for every individual element at risk is impossible since the required data (i.e. a dataset that shows the relationship between flood impacts and resistance factors) is not available. Even if the data were available, the analysis would be time-consuming as it would need a considerable effort. Therefore, the exposed components should be classified into homogeneous groups, and damage assessment should be done for each class of element at risk. This homogeneity can be discussed based on the similarity of the behaviour against the impacts of flood for one class and a significant difference compared to other classes (Merz et al., 2010). In this regard, Smith (1994) proposes that the socioeconomic factors (e.g. household income) of the population in a region with a significant variation of dwelling types, like the UK, may influence the resistance of one economic sector (e.g. residential buildings) (Smith, 1994). Thus, considering a higher level of classification could be useful. Further, Kreibich and Dimitrova (2010) and Kreibich and Thieken (2008) recommend the classification of damaged components based on inundation types (e.g. flash flood, overland flow, riverine flood) (Kreibich and Dimitrova, 2010; Kreibich and Thieken, 2008). The other important factor is the availability of data. Defining very detailed classes without having the support of sufficient data leads to a high level of uncertainty in the outcome.

Accordingly, an initial classification can be done based on the social and/or economic functions of affected areas (e.g. residential buildings, commercial buildings, industrial buildings, public sectors, infrastructure and agriculture). This categorisation, as explained earlier, is recommended due to the different characteristics and their behaviour, and the variation in flood damage-influencing parameters. For instance, while studies show that water depth is the most significant damage-influencing parameter for urban residential buildings (Cammerer et al., 2013), damage to agricultural plants is mostly dependent on the time and duration of the flood (Merz et al., 2010). Further to this classification, each category, as discussed above, can also be divided into sub-classes. For instance, FLEMOps and FLEMOcs, two German models

for the private and commercial sectors, have defined some sub-classes based on the size of the property, the type of dwelling, the quality of structure, and the function of the building (Kreibich et al., 2010; Thielen et al., 2008).

Geoscience Australia (GA) has developed some damage models for residential and industrial buildings, and the sub-classes are defined based on the size of buildings, the construction materials, the presence of garages, and the number of storeys (Geoscience Australia, 2012). The United States Federal Emergency Management Agency (FEMA) and Army Corps of Engineers (USACE) defines the detailed classes based on the number of storeys and the presence or absence of a basement (USACE, 2003).

2.3.3 Damage-influencing parameters

Damage-influencing parameters can be grouped into flood actions and building resistance parameters (Table 2-2). The most significant actions of the flood, depending on the inundated area as discussed above, are water depth, lateral pressure, flow velocity, flood duration, water contamination, sediment load, timing, and inundation frequency (Gissing and Blong, 2004; Kelman and Spence, 2004; Merz et al., 2013). The resistance parameters could be classified as building characteristics, private precaution, early warning, emergency measures, flood experience and socioeconomic status (Hasanzadeh Nafari et al., 2016c; Thielen et al., 2005). The resistance factors which represent the capacity or incapacity of an inundated object against the impacts of the flood may be independent of or dependent on each other (e.g. individual preparedness and early warning are not independent of each other). Thus, flood damage assessment is a complicated process and understanding the single or joint effects of the influencing parameters needs a comprehensive analysis. However, most of the available traditional methods have neglected these parameters, relying only on the type and function of objects at risk and the stage of flood water. The reason could be related to a general tendency for using a simplified approach in the industry (e.g. stage-damage functions), or a lack of reliable data (Cammerer et al., 2013; Hasanzadeh Nafari et al., 2016c).

Nevertheless, some studies have attempted to consider more damage-influencing parameters. In this regard, Wind et al. (1999); Penning-Rowsell and Green (2000); Smith (1994); and Parker et al. (2007) attempted to evaluate the effects of some non-structural resistance measures such as early warning and private precaution (Parker et al., 2007; Penning-Rowsell and Green, 2000; Smith, 1994; Wind et al., 1999). The FLEMO multi-parameter model from Germany (i.e. for private and commercial sectors in the micro- and meso-scale), the conceptual model of Nicholas et al. (2001) from the UK, and the non-calibrated model of Zhai et al. (2005) in Japan are other examples (Elmer et al., 2010; Kreibich et al., 2010, 2007, 2005; Kreibich and Thieken, 2008; Nicholas et al., 2001; Seifert et al., 2010; Thieken et al., 2008, 2006, 2005; Zhai et al., 2005). Recently, Vogel et al. (2013) used a Bayesian network, and Merz et al. (2013), Chinh et al. (2015), and Hasanzadeh Nafari et al. (2016c) used tree-based data mining approach to analyse the whole gamut of influencing factors, and assess their single or joint effects in a more comprehensive way (Chinh et al., 2015; Hasanzadeh Nafari et al., 2016c; Merz et al., 2013; Vogel et al., 2013).

Table 2-2: Damage-influencing parameters including flood impacts and resistance factors

Divisions		Influencing Parameters
Impact parameters	Hazard intensity	Depth
		Velocity
		Contamination
		Duration
		Sediment load
		Frequency
		Timing
Resistance parameters	Emergency measures	Emergency actions
	Precaution and experience	Precaution actions
		Former flood experience
	Building specifications	Quality of property
		Value of property
		Floor space per person
	Socioeconomic situation	Residents need assistance
		Ownership status
		Monthly income
		Low education residents

2.3.4 Cost assessment

Traditionally, two approaches are identified for the assessment of direct damages: averaging method and stage-damage function (Molinari, 2011). In Australia, the rapid appraisal method (RAM) is the most common averaging model for the estimation of direct losses (Sturgess and Associates, 2000). The method recommends an average value of damage for every flooded building. While the method is inexpensive and

helpful for rapid assessment, the outcomes are uncertain and inaccurate (Barton et al., 2003; Gissing and Blong, 2004).

Although flood damage assessment is a complicated process, the stage-damage function due to its simplicity is an internationally accepted approach for flood loss estimation (Cammerer et al., 2013; Thielen et al., 2006). Stage-damage functions depict a causal relationship among flood actions (e.g. the depth of water), vulnerability features (e.g. the building type), and the extent of losses (i.e. the percentage of damage or the monetary value of loss) (see Fig. 2-6) (Jongman et al., 2012a; Smith, 1994).

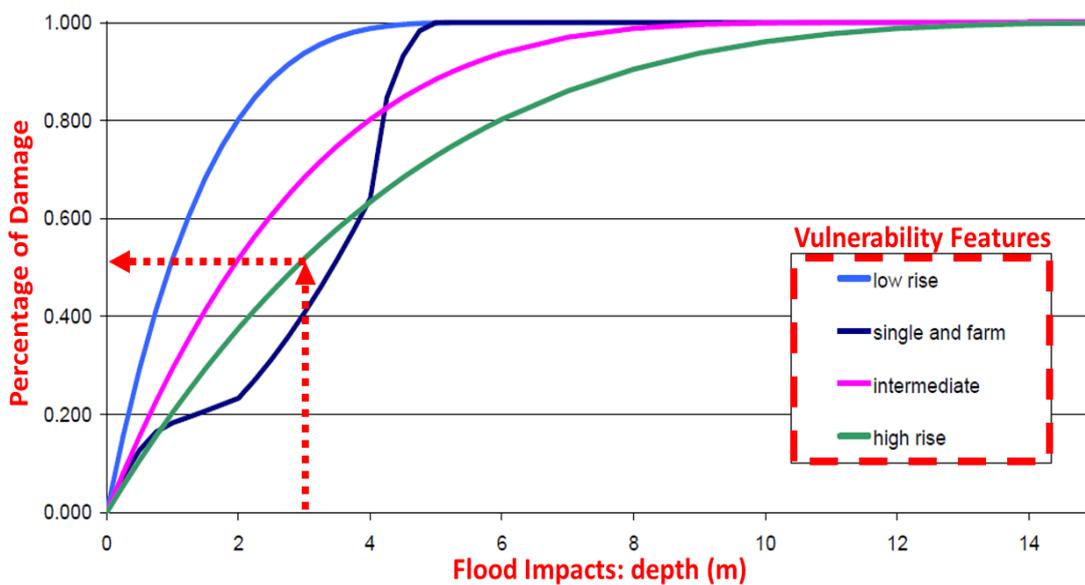


Figure 2-6: Visualisation of a relative stage-damage function

Damage functions are classified as relative or absolute, and as empirical or synthetic. Relative functions express the magnitude of losses as a percentage of the total value of the damaged property (i.e. the depreciated value or the replacement cost), while absolute functions show the extent of damages in fiscal values (André et al., 2013; Hasanzadeh Nafari et al., 2017). The FLEMO, HAZUS and USACE methods are examples of the first type (Kreibich et al., 2010; Scawthorn et al., 2006; Thielen et al.,

2008; USACE, 2003) and an example for the second approach is ANUFLOOD (Smith, 1994). Empirical functions (e.g. ANUFLOOD) are derived based on real damage data collected from real-world events, while the synthetic method (e.g. Geoscience Australia) relies on an analytical approach and what-if questions to estimate the magnitude of damage for every stage of water (e.g. what is the level of damage if the stage of water reaches to 1-m above the first floor). It is possible to have an empirical-synthetic method which combines both approaches (e.g. USACE) (Hasanzadeh Nafari et al., 2017). All these approaches have advantages and disadvantages, which are compared below (Table 2-3 and 2-4).

As stated earlier, many researchers have attempted to improve the accuracy and transferability of stage-damage functions by moving away from a traditional approach (i.e. relying only on the type or use of a flooded object and the stage of water) into a new approach which uses multi-parameters and probabilistic analysis (Schröter et al., 2014a). Furthermore, tree-based models and Bayesian network techniques have been used recently for studying the influencing parameters and predicting the extent of damages.

Flood loss models (whether stage-damage functions or tree-based models) are sharply restricted to the features of the area of origin (i.e. flood features and building characteristics) (Hasanzadeh Nafari et al., 2016a). Thus, transferring the damage models to a new study area and/or a new flood event does not result in an accurate relationship between the extent of damages and the impacts of flood, unless the models have been calibrated with an empirical dataset collected from the new case study (Cammerer et al., 2013; Luino et al., 2009; Oliveri and Santoro, 2000). This loss of accuracy naturally reduces predictive capacity (Schröter et al., 2014b). On the other hand, the largest effect on loss estimation is induced by the shape of the applied damage models, while precision in collecting hydraulic input and flood characteristics is of minor importance (Apel et al., 2009; de Moel and Aerts, 2011). Therefore, validation of flood loss models is one important step in model development (Cammerer et al., 2013; Schröter et al., 2014b). However, due to a lack of historical data, little research has been done on the

validation of models, especially when they are subjected to temporal and/or spatial transfer (Merz et al., 2010; Meyer et al., 2013; Seifert et al., 2010; Thieken et al., 2008), and Australia is no exception.

Table 2-3: Advantages and disadvantages of empirical and synthetic models (Merz et al., 2010)

	Advantages	Disadvantages
Empirical models	<p>Greater accuracy due to utilisation of real damage data.</p> <p>Effects of damage reduction options can be considered.</p> <p>Variability of the real-world objects and uncertainty of the empirical data can be taken into consideration.</p>	<p>Data collection is challenging since post-disaster damage survey is not a common activity.</p> <p>Need for extrapolation due to a lack of information about different types of flood.</p> <p>Rigid for transferring in space or time due to the variation of the building characteristics and mitigation measures.</p>
Synthetic models	<p>Damage calculation is possible for every stage of water.</p> <p>More flexible for transferring in space or time due to the independence of real-world data.</p>	<p>Data gathering and detailed analysis are complicated and time-consuming even for one type of building.</p> <p>Effect of flood damage mitigation measures is neglected.</p> <p>The subjective analysis may lead to the uncertain estimation of loss.</p>

Table 2-4: Advantages and disadvantages of relative and absolute models (Merz et al., 2010)

	Advantages	Disadvantages
Relative models	<p>More flexible for transferring in space or time due to the independence of market variations.</p> <p>Simplicity in use for different purposes.</p>	<p>Asset value is needed for multiplying by the damage ratios, and this matter may add additional uncertainty.</p>
Absolute models	<p>Asset value is not required, and damage monetary values can be calculated directly.</p>	<p>More rigid for transferring in space or time.</p> <p>Need regular re-calibration due to inflation and changes in market values.</p>

2.4 Economic Sectors

As stated above, one of the main influencing factors for model classification is the economic activity of the exposed object. Studies show that the behaviour (i.e. resistance or vulnerability) of inundated properties against the impacts of flood and the type of assets are a function of the property's economic function. Thus, sector-based categorisation is a mostly accepted method of model classification. The most common economic sectors utilised for this classification are the residential sector, industrial sector, commercial sector, public service, lifelines, infrastructure and agriculture sector (Merz et al., 2010).

The summary of the aspects of flood loss estimation is represented in Table 2-5.

➤ **The focus of this study is on ex-ant direct, tangible damages of the flood in urban areas. The spatial extent of damage estimation processes is on the micro-scale, and the target economic sectors are residential and commercial building structures.**

Accordingly, in the next sections, the existing flood damage models related to the residential and commercial economic sectors which are frequently used in the world and Australia will be compared and discussed.

Table 2-5: Summary of the aspects of flood loss estimation

Damage category	Damage type	Spatial Scale	Economic value	Timing	Exposure	Influencing parameters	Development	Economic sectors
Direct	Potential	Micro	Replacement	Ex-ante	Social	Flood impacts	Relative	Residential
Indirect	Actual	Meso	Depreciated	Ex-post	Economic	(e.g. depth, and velocity)	Absolute	Industrial
Tangible		Macro			Environmental		Empirical	Commercial
Intangible						Resistance factors	Synthetic	Public
						(e.g. material and early warning)	Empirical-synthetic	Lifeline Infrastructure Agriculture

2.4.1 Residential sector

The residential sector has attracted the attention of most researchers since a considerable portion of urban flooding losses is dedicated to residential buildings. Accordingly, in this study, only a few well-known examples will be compared. The RAM model is an averaging method from Australia. This model recommends an average value of potential damage (\$20,500) for every inundated residential building. This value of damage includes damages to contents and the structure, and it should be applied to all flooded buildings including those flooded above or below the first-floor level. The method is empirical-synthetic, and the extent of potential losses could be changed to actual values using recommended coefficients based on the previous experiences of flooding and the effective time of early warning (Hasanzadeh Nafari et al., 2016a; Sturgess and Associates, 2000).

FLEMOps is an empirical relative damage model. The empirical data has been collected by computer-aided telephone interviews from 1697 flooded households after the August 2002 event (see Fig. 2-7). The influencing parameters considered in this model are water depth (five groups), water contamination (three groups), building type (three categories), building quality (two classes) and private precaution measure (three levels) (Thieken et al., 2008).

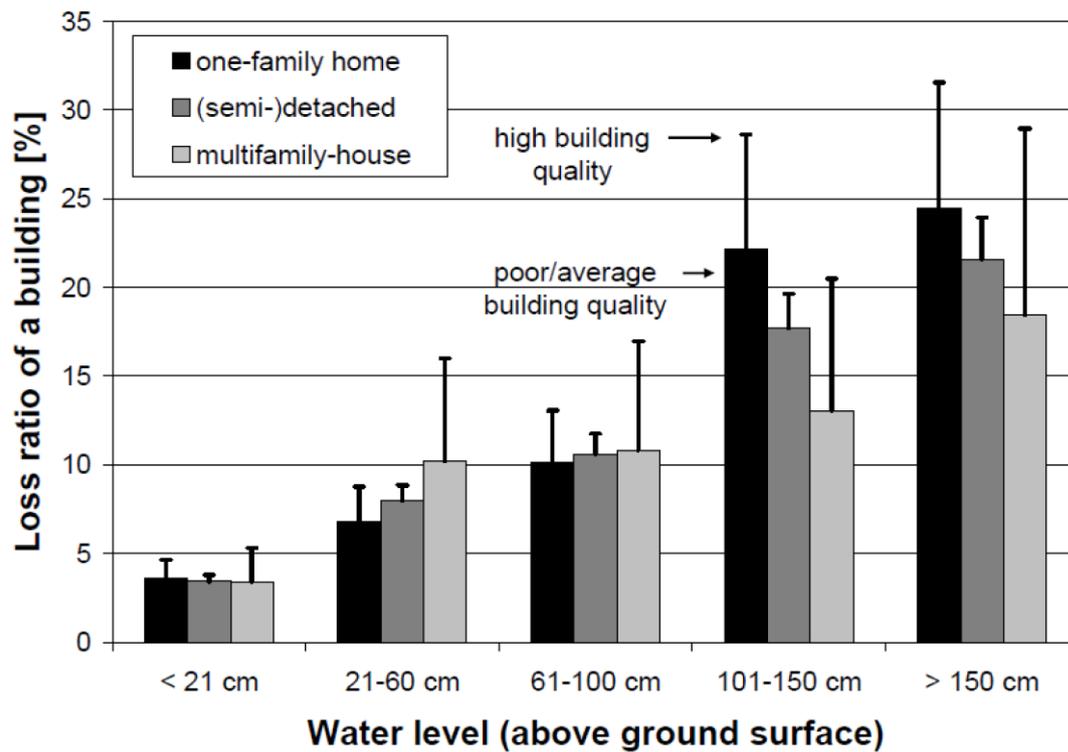


Figure 2-7: FLEMOps model for the estimation of residential building structures flood losses (Thieken et al., 2008)

USACE is a model developed by the United States Federal Emergency Management Agency (FEMA) and Army Corps of Engineers (USACE). This model is an empirical-synthetic approach that expresses the magnitude of losses as a percentage of building value. The considered parameters are the depth of water, the number of storeys and the presence of garage (Fig. 2-8). Also, the model represents the percentage of damage for building fabrics and contents separately (Comiskey, 2005; USACE, 2003).

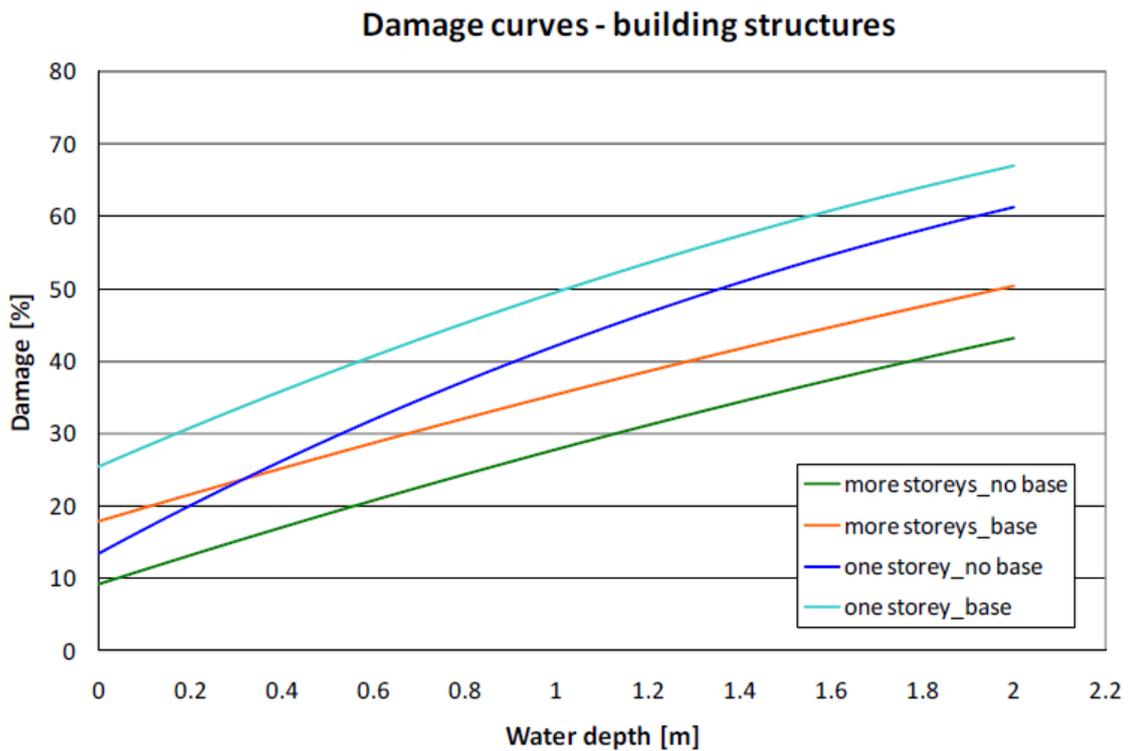


Figure 2-8: USACE model for the estimation of residential building structures flood losses

The other model has been derived by Geoscience Australia (GA) for Queensland and South Sydney. It is a synthetic relative model that represents the damage of building structure and contents separately. This method has classified the stage-damage functions based on some properties of buildings such as material, size, number of storeys and availability of a basement. Also, water depth is the only hydraulic input of this model (see Fig. 2-9) (Geoscience Australia, 2012).

Table 2-6 shows the summary of the comparison of four flood damage models for residential sector.

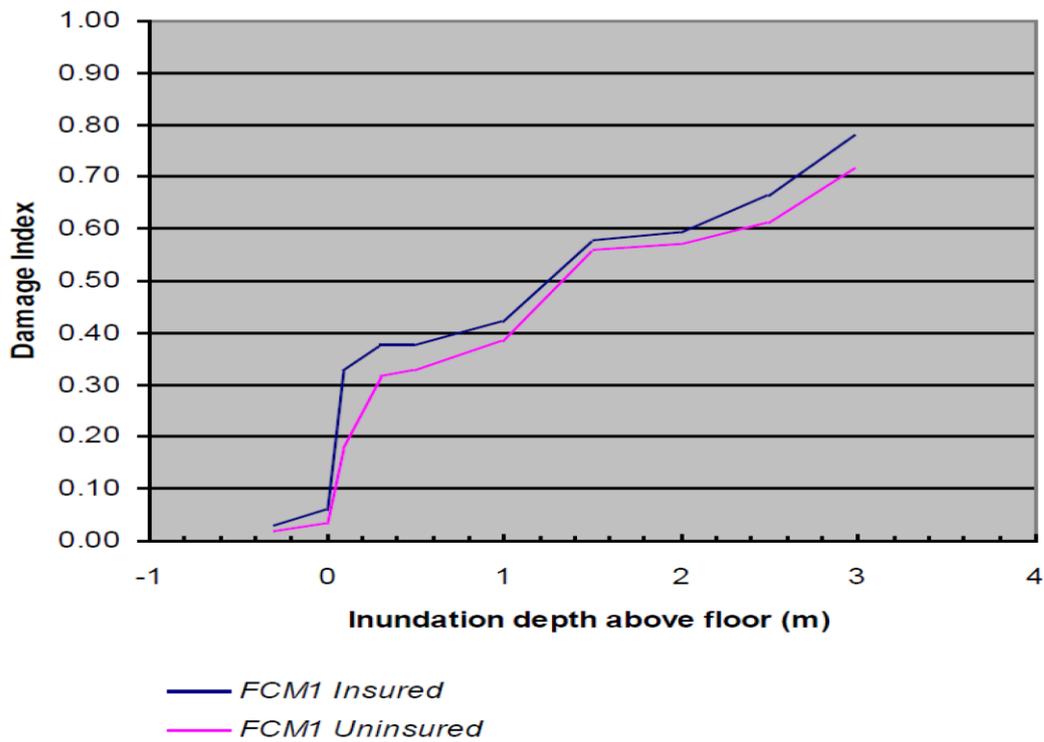


Figure 2-9: GA model for the estimation of residential building structures flood losses (FCM1: one storey, raised timber floor, lightweight cladding, no basement) (Geoscience Australia, 2012)

Table 2-6: Comparison of four flood damage models for residential sector

Model	Country	Development	Function Type	Influencing Parameters
FLEMOps	Germany	Empirical	Relative	water depth, water contamination, building type, building quality, and private precaution measure
GA	Australia	Synthetic	Relative	water depth and building type (material, size, number of storeys, and availability of basement)
USACE	USA	Empirical-synthetic	Relative	water depth and building type (number of storeys, and availability of basement)
RAM	Australia	Empirical-synthetic	Absolut	lead time, flood experience

Knowledge gaps in Australian models

The gaps which are recognised in Australian models are as follows (Hasanzadeh Nafari et al., 2016b):

- Due to a lack of empirical data most damage models are synthetic, they are not calibrated with empirical data, and few studies have been conducted on the validation of results;
- Most approaches are absolute which is more rigid and does not easily transfer across time and space;
- To the best of our knowledge, all approaches are of the traditional type which relies only on a deterministic relationship between the type or use of properties at risk and the depth of water;
- The interaction of most damage-influencing parameters and the uncertainty of data are neglected.

As is discussed in more detail below, this study has attempted to address the above issues and to close the gaps.

2.4.2 Commercial and industrial sector

This part of the study has also compared some well-known flood damage models for the estimation of commercial building flood losses. In Australia, RAM and ANUFLOOD are the most commonly used flood damage models. As explained previously, RAM is an averaging method which considers some mean values of damage for each inundated building. The mean values are the total value of the structural and content losses and should be applied to all inundated buildings including those flooded above or below the first-floor level. For commercial buildings with an area less than 1000 m² the suggested damage value is the same as for residential buildings (\$20,500). However, for large commercial buildings with an area more than 1000 m² in size, the method has suggested three values (\$45, \$80, and \$200 per square meter) of damage depending on the value of contents in the property (see Table 2-7). All damage values are potential losses, and they can be converted to actual losses using some coefficients

and by considering the previous experiences of flooding and the early warning time (Hasanzadeh Nafari et al., 2016a; Sturgess and Associates, 2000).

Table 2-7: Average potential damage for large commercial buildings (Sturgess and Associates, 2000)

Value of contents	Mean potential damages per m² (includes external, internal contents and structural)
Low (e.g. offices, sporting pavilions, churches)	\$45
Medium (e.g. libraries, clothing businesses, caravan parks)	\$80
High (e.g. electronic, printing)	\$200

ANUFLOOD (Smith, 1994) is an empirical approach prepared based on the data from the 1986 flood event in Sydney. Similar to RAM, this approach is an absolute model which estimates the total value of damage including structural and content losses. ANUFLOOD represents some potential stage-damage functions classified based on the size of the property (i.e. smaller than 186 m², between 186 m² and 650 m², and larger than 650 m²) and the vulnerability of the business's contents. Damage values, for small- and medium-sized businesses are expressed in dollars; while for the large-sized properties, the values are given in dollars per square metre. Similarly to RAM, the potential damage costs could be changed to actual values using some convert coefficients (Bureau of Transport Economics, 2001; Gissing and Blong, 2004; Hasanzadeh Nafari et al., 2016a).

The other method considered in this study is FLEMOcs (Kreibich et al., 2010). This multi-parameter stage-damage function is a relative empirical method derived based on the data collected from 642 inundated businesses via telephone surveys after the floods of 2002, 2005 and 2006 in Germany. This method defined five classes of water depth (<21 cm, 21–60 cm, 61–100 cm, 101–150 cm, and >150 cm), three groups of company size (1–10, 11–100, >100 employees), and four categories of economic activity (public

and private sectors; production industry; corporate services and trade). Based on these classifications, the magnitude of damage could be estimated separately for buildings, equipment and goods (products and stock) (Fig. 2-10). Also, the impacts of water contamination and private precautions could be taken into consideration by using some scaling coefficients (Hasanzadeh Nafari et al., 2016a; Kreibich et al., 2010; Seifert et al., 2010).

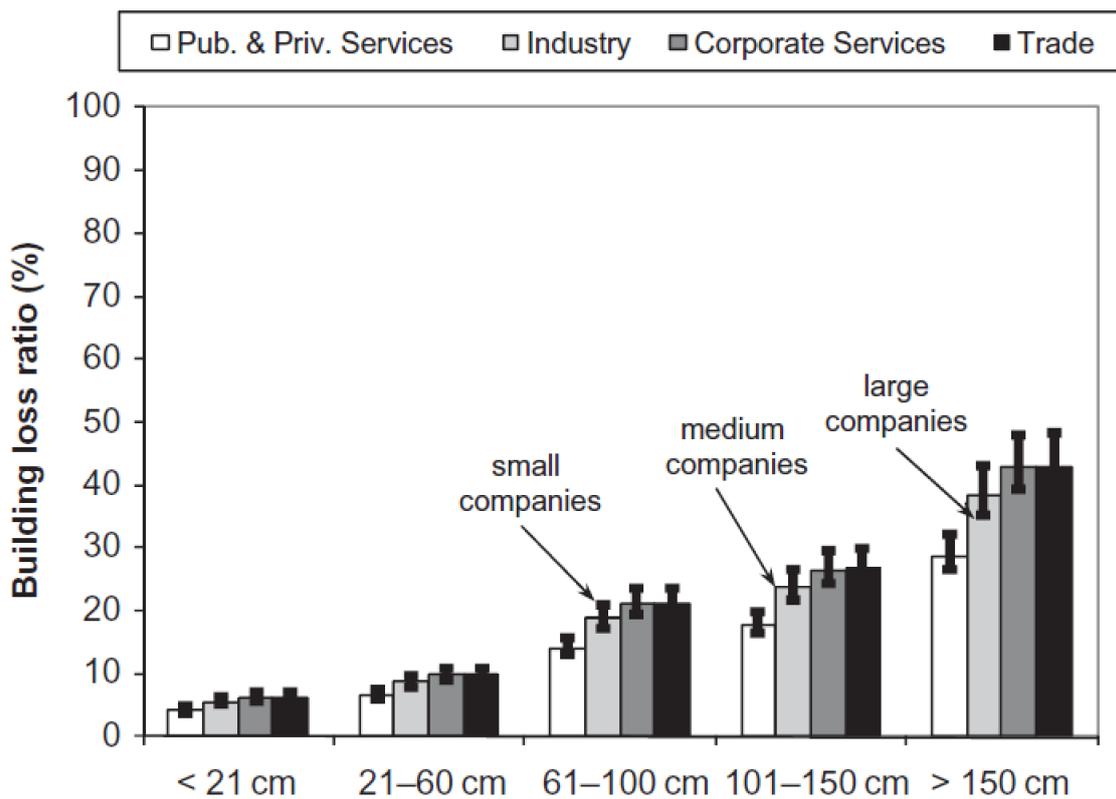


Figure 2-10: FLEMOcs model for the estimation of commercial building structures flood losses (Kreibich et al., 2010)

Table 2-8 shows the summary of the comparison of three flood damage models for the commercial sector.

Table 2-8: Comparison of three flood damage models for the commercial sector (Merz et al., 2010)

Model	Country	Development	Function Type	Influencing Parameters
FLEMOcs	Germany	Empirical	Relative	water depth, water contamination, company size, economic sector, and private precaution measure
ANUFLOOD	Australia	Empirical	Absolute	water depth, company size, the vulnerability of the contents
RAM	Australia	Empirical-synthetic	Absolute	company size, content value, lead time, flood experience

Knowledge gaps in Australian models

The gaps which are recognised in the most commonly used Australian models are identified as follows (Hasanzadeh Nafari et al., 2016a):

- The RAM method, due to neglecting the variation in hydraulic impacts and the differences of building resistance parameters, does not represent the distribution of the losses over a flooded area. Also, its outcome is uncertain and inaccurate;
- Most approaches (e.g. RAM and ANUFLOOD) are of the absolute type which is more rigid and does not easily transfer across time and space, or they are of the non-calibrated synthetic type;
- Most approaches calculate the total potential value of losses including building and content damages. Thus, due to the different nature of movable contents from structural fabrics with lead-time, the exchange of potential losses into actual values is problematic;

- To the best of my knowledge, all approaches have neglected the uncertainty of data, and they have been derived based on a deterministic relationship between type or use of properties at risk and depth of water.

As is discussed in more detail below, this study has attempted to address the above issues and to close the gaps.

2.5 Conclusions

The previous parts of this study covered the related definitions of flood loss estimation, discussed the general procedure for flood damage assessment, clarified the focus of this study, reviewed some well-known methods of flood cost estimation and listed the most significant gaps in Australian approaches. The following key issues and suggestions could be concluded:

- Flood damage is a complicated process and is controlled by a variety of influencing parameters which are mostly neglected. This matter has been distinguished as a source of uncertainty and requires more attention. The most influential parameters could be classified into flood intensity factors including depth of water, flow velocity, return period, duration, frequency and contamination of water; and building flood-resistant indicators including the materials and characteristics of the property, individual precautionary and emergency actions, early warning time and preparedness, and the former flood experience and socioeconomic situations of residents. Accordingly, data mining techniques and multi-parameter damage models should be used for exploring the interaction and the importance of different damage-influencing parameters, and understanding the flood loss processes.
- Considering the variability of the real-world and the uncertainty of the data as other important steps in improving models. Accordingly, relying on probabilistic rather than deterministic methods, and increasing the size of datasets using random sampling approaches, are recommended.

- Developing a relative empirical-synthetic model leads to a better level of accuracy in results and transferability in time and space. The new model should be simplified enough for understanding, updating or performing modifications based on the variability of the geographical conditions across the world.

Ultimately, the main sources of uncertainty of flood damage models could be related to the lack of reliable damage data, the transfer in the geographical area of damage models, the use of invalidated models, and variability in real-world events and behaviours (Cammerer et al., 2013; Merz et al., 2010; Meyer et al., 2013). Considering the above-mentioned suggestions and issues, this study has attempted to develop some new flood loss estimation models for the geographical conditions (i.e. flood characteristics, non-structural resistance parameters, and building specifications) of Australia with better performance, which enhances the accuracy of the outcome and the reliability of the results.

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Chapter 2: Literature Review

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3 CALIBRATION AND VALIDATION OF FLFA_{rs}

A NEW FLOOD LOSS FUNCTION FOR AUSTRALIAN
RESIDENTIAL STRUCTURES [Published Chapter]¹

3.1 Abstract

Rapid urbanisation, climate change and unsustainable developments are increasing the risk of floods. Flood is a frequent natural hazard that has significant financial consequences for Australia. The emergency response system in Australia is very successful and has saved many lives over the years. However, the preparedness for natural disaster impacts in terms of loss reduction and damage mitigation has been less successful. In this chapter, a newly derived flood loss function for Australian residential structures (FLFA_{rs}) has been presented and calibrated by using historic data collected from an extreme event in Queensland, Australia that occurred in 2013. Afterwards, the performance of the method developed in this work (contrasted to one Australian model and one model from the USA) has been compared with the observed damage data

¹ Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016. Calibration and validation of FLFA_{rs} – a new flood loss function for Australian residential structures. *Nat. Hazards Earth Syst. Sci.* 16, 15–27

collected from a 2012 flood event in Maranoa, Queensland. Based on this analysis, validation of the selected methodologies has been performed in terms of Australian geographical conditions. Results obtained from the new empirically based function (FLFA_{rs}) and the other models indicate that it is apparent that the precision of flood damage models is strongly dependent on selected stage-damage curves, and flood damage estimation without model calibration might result in inaccurate predictions of losses. Therefore, it is very important to be aware of the associated uncertainties in flood risk assessment, especially if models have not been calibrated with real damage data.

3.2 Introduction

Studies have shown that compared to other types of natural hazards, floods are a considerable threat to a nation's economy, the built environment, and people (André et al., 2013; Kourgialas and Karatzas, 2012; Llasat et al., 2014; UNISDR, 2009). Furthermore, in recent decades, the flood risk due to climate change and the growth in value and vulnerability of exposed properties has been increasing exponentially (Elmer et al., 2012; Kundzewicz et al., 2005), which subsequently raises the significance of flood risk management. Flood damage assessment in order to mitigate the probability of expected losses is an important part of the risk management process (André et al., 2013; Elmer et al., 2010; Kaplan and Garrick, 1981), and the results will provide decision-makers, emergency management organisations, and insurance and reinsurance companies with a tool for planning better risk mitigation strategies to cope with future disasters (Emanuelsson et al., 2014; Merz et al., 2010).

In general, there is no common agreement among terms such as damage, loss and impact, but flood damage can either be categorised as direct or indirect. The direct category occurs due to physical contact between the floodwater and the inundated objects, and the indirect category is based on the effects of direct damage on a wider scale of space and time (Meyer et al., 2013; Molinari et al., 2014a; Thielen et al., 2005). Both categories can be evaluated as marketable (tangible) or non-marketable

(intangible) values (André et al., 2013; Kreibich et al., 2010). The focus of this chapter is on direct, tangible damages to residential building structures due to a short duration of riverine (low-velocity) inundation.

Direct tangible damages of floods before they occur can be estimated by an averaging method such as the rapid appraisal method (RAM) or by function approaches such as depth-damage curves (Molinari, 2011). The RAM is a simplified method for flood damage estimation in the absence of data required for using depth-damage curves (Sturges and Associates, 2000). This method considers mean unit values of damage for all buildings in the inundated area. Although RAM is useful for early assessment of the magnitude of damage, the results are considerably inaccurate (Barton et al., 2003).

The function approach is a common and internationally accepted methodology for estimating the relative or absolute value of losses via a causal relationship among the magnitude of the hazard (e.g. the depth of water), the level of vulnerability (e.g. the building type), and the expected damages (Dewals et al., 2008; Jongman et al., 2012; Kreibich and Thieken, 2008; Molinari et al., 2014b; Smith, 1994; Thieken et al., 2006). This approach varies from traditional functions, i.e. functions which are solely based on the type or use of an element at risk and the water depth, to multi-parameter probabilistic loss models (Merz et al., 2013; Schröter et al., 2014). It is worth noting that these functions are strongly restricted to the area of origin, and transferred functions to a new geographical condition do not establish an appropriate relationship between the magnitude of the flood and the value of losses unless they have been adapted and calibrated with the conditions of the new region of study (Cammerer et al., 2013; Molinari et al., 2014b). Therefore, one important step in model development is model validation. In general, obtaining a reliable estimation of flood consequences by using a depth-damage function with an accurate and calibrated shape is considered more necessary than precision in collecting hydraulic inputs and flood characteristics (Apel et al., 2009).

Due to a lack of historic data, few studies have been conducted to explore the validation of well-known overseas methodologies in other flood-prone regions

(Cammerer et al., 2013), and also for calibrating local Australian methodologies with empirical data. This chapter aims to present a new flood loss model (FLFA_{rs}) for the Australian geographical conditions by using historic data collected from an extreme event that occurred in the Bundaberg region of Queensland, Australia in 2013. In addition, the accuracy of the results obtained from the newly derived model and two existing models was compared using historic data collected from the Maranoa flood event (2012).

3.3 Background

Stage damage curves have been grouped into two main classifications: empirical and synthetic curves. Empirical curves build on surveyed damage data. They estimate the actual damage as they take into account the effect of mitigation measures. Also, variability within one category of building and water depth is reflected by the surveyed damage data (Kreibich et al., 2005; Merz et al., 2010, 2004). However, Smith (1994) discussed that by moving in time and space, the warning time, level of preparedness in society, and the characteristics of a building could vary considerably. Therefore, gathering data from one actual flood event and using it as a guide for future events in a new area of study, or even in the area of origin, requires a complicated process of extrapolation (Gissing and Blong, 2004; Smith, 1994). In other words, extrapolation of empirical damage curves to different regions is difficult due to differences in the level of precaution and differences in building characteristics (Barton et al., 2003). As a solution, synthetic curves based on a valuation survey have been created for different types of buildings. Valuation surveys refer to the value and elevation of all components that are located above the basement. This means that by using valuation surveys, an average distribution of building fabrics in the height of the structures would be extracted (Barton et al., 2003). Afterwards, the magnitude of potential damage for different water levels via “what-if” questions is estimated based on their average distribution in the height of the structure and the level of vulnerability of each component (Gissing and Blong, 2004; Merz et al., 2010).

Based on the valuation survey, several synthetic local damage curves have been prepared for Queensland, Victoria and New South Wales. Most of the synthetic methodologies prepared for Australia are not calibrated with empirical loss data, and few studies have been done on result comparison and uncertainty estimation. As mentioned earlier, these curves will estimate the potential damage based on “what-if” questions. Potential losses are the maximum possible value of losses without considering any mitigation measures (Bureau of Transport Economics, 2001; Molinari, 2011; Molinari et al., 2013). Usually, potential damage is the greatest value of losses, and its magnitude is more than the actual damage (Molinari, 2011; Molinari et al., 2013). To address this issue and increase the level of accuracy, FLFA_{rs} has been calibrated with an empirical database.

Functional approaches can also be categorised as absolute and relative types. Absolute functions express the magnitude of damages in monetary values, while relative types estimate the dimension of losses as a ratio of the total value, i.e. replacement value or depreciated value (Kreibich et al., 2010). Almost all of the approaches available in Australia are absolute. These types of curves, compared to relative damage curves, are less flexible for moving in the spatial scale or time since they are dependent on changes in market values (Merz et al., 2010). For instance, the RAM report (Sturgess and Associates, 2000) claims that the magnitude of damage estimated by ANUFLOOD curves (Gissing and Blong, 2004; Smith, 1994) should be increased by 60%. The reason for this is related to the fact that these curves were prepared based on data from a 1986 flood in Sydney, and also due to changes in the value of the dollar compared to today’s value. Hence, their results are no longer reliable. Also, some updated absolute approaches such as that used in Nerang, Queensland, prepared by Gold Coast City Council (Barton et al., 2003), are restricted to the area of origin. In transferring such curves to a new study area of Australia, the differences in the replacement value of the exposed items or repair costs of assets will decrease the reliability of the results. With regard to moving in space or time, and compared to the available methodologies, the authors have tried to increase the level of flexibility of the newly derived model.

A general lack of data regarding the logic behind existing state reports and their methods is observed by end users and researchers in Australia. To be more precise, a number of methods have been identified, such as the Geoscience Australia model (Geoscience Australia, 2012), and the NSW government curves (Office of Environment and Heritage; New South Wales Government, 2007), but no specific detailed literature has been published about them. However, the new method developed in this research (FLFA_{rs}), in addition to its flexibility and transferability in time and space, is simple enough to understand and generalise to other types of buildings and vulnerability classes.

Although the detailed valuation survey proposed by Smith (1994) seems a little complicated and time-consuming even for data gathered from one type of building (Merz et al., 2010), the new model for evaluating the assembly items and tracking the vertical parameters by considering more general categories, has attempted to simplify the process as much as possible.

3.4 The Newly Derived Loss Model (FLFA_{rs})

The residential synthetic stage-damage curves can be developed by employing the following steps (Bureau of Transport Economics, 2001):

- Based on the characteristics of buildings in the area of study (e.g. material and size), some representative classes should be selected.
- For each selected class, an average distribution of the assembly items in the height of the buildings should be extracted.
- Finally, based on the average value of the flooded items relative to the total value of the building and the degree of fragility of each item, stage-damage curves for different depths of water can be constructed.

As mentioned above, the disadvantage of the synthetic methodology may be attributed to the significant effort in gathering data and details for the valuation survey, in addition to ignoring the effect of early warning and damage mitigating actions (Merz et al., 2010). For resolving the first issue, a more general and simplified method has

been followed by this study. For resolving the second issue, the results of this study have been calibrated with the relevant empirical data set. To be more specific, four common vulnerability classes and building types for the selected area of study in Australia have been considered:

- one-storey buildings with masonry walls and slab-on-ground construction;
- two-storey buildings with masonry walls and slab-on-ground construction;
- one-storey buildings with timber walls and slab-on-ground construction; and
- two-storey buildings with timber walls and slab-on-ground construction.

This selection has been made based on the data collected from the national exposure information system of Australia (Dunford et al., 2014). This data set shows that 74 % of residential buildings in our areas of study are made with masonry and timber walls. Moreover, 99 % of these buildings are one and two- storeys high. Also, assembly items of the buildings based on the proposal of the HAZUS technical manual (FEMA, 2012) have been categorised into five general groups:

- foundation and below first floor, which includes site work, footings, walls, slab, piles, and items that are located below the first floor of the structure;
- structure framing, which includes all of the main load carrying members below the roof and above the foundation;
- roof covering and roof framing;
- exterior walls, which includes wall coverings, windows, exterior doors and insulation; and
- Interiors, which includes interior walls and floor framing, drywall, paint, interior trims, floor coverings, cabinets, and mechanical and electrical facilities.

The general methodology is to describe the damage for each stage of water using a general function. Based on the recommendations of the HAZUS technical manual (FEMA, 2012) and the knowledge of experts, different sub-assembly groups start damaging in different stages of flood. In other words, the first non-zero percentage of damage for each group will occur after a specific level of total damage of the building

and subsequently to different water depths. This fact shows that the slope of the damage curves could vary based on an exponential equation (Cammerer et al., 2013; Elmer et al., 2010; Kreibich and Thieken, 2008). On the other hand, as described in detail by the HAZUS technical manual and the Australian construction cost guide (Rawlinsons, 2014), the replacement value of interiors and exterior walls, which start damaging from the first stage of water, are about 70 % of the total replacement value of the building. This means that for the first few metres of flood, the rate of damage due to storing the utility facilities is greater than the remaining stages. Therefore, the power of the following exponential equation (1) can control the rate of change in the percentage of damage compared to the increment of water depth. The accurate value of r for each vulnerability class will be extracted based on empirical data, but we can say that in general, a higher value for r means faster inclines at lower depths, which results in damage occurring more quickly in the first few metres of each floor. The formula for a one-storey building could be considered as

$$d_h = \left(\frac{h}{H} \right)^{\frac{1}{r}} \times D_{\max} \quad (1)$$

where d_h is the percentage of damage corresponding to the depth of water, h the depth of water, H the maximum height of the building, D_{\max} the maximum percentage of damage corresponding to the maximum height of the building, and r is the rate control.

In typical residential buildings (urban buildings that are generally uniform from the second floor) with more than one storey, the first floor of the building contributes more damage than the other stories because most utilities and electrical equipment are stored there, as well as in the basement. Therefore, this formula enables the user to define the level of damage that would occur between the first-floor elevation and the top of the rafters of the first floor, and how much typical damage will be distributed among the other storeys. The generalised formula for damage estimation in each storey of a

building based on the maximum percentage of damage and the appropriate value for rate control r can be expressed as:

$$d_{hi} = \left(\frac{h_i}{H_i} \right)^{\frac{1}{r_i}} \times D_{\max i} \quad (2)$$

where d_{hi} is the percentage of damage for the i_{th} floor corresponding to the depth of water above the i_{th} floor, h_i the depth of water above the i_{th} floor, H_i the height of the i_{th} floor, $D_{\max i}$ the maximum percentage of damage for the i_{th} floor, and r_i is the rate control for the i_{th} floor.

Overall, for this concept, the authors have tried to create a simple and flexible curve with regards to the variability in the number of storeys, height of storeys, and the distribution of components through the height of the building. Therefore, users can manipulate and calibrate this model easily based on the characteristics and types of buildings for other areas of study.

3.5 Study Areas and Official Loss Data

3.5.1 Study Areas and Flood Events

For this study, two areas have been selected. The first study area is Bundaberg city in Queensland, Australia. Location of this city, as illustrated in Fig. 3-1, is part of the Bundaberg region located north of the state's capital, Brisbane. The economy of the Bundaberg region is mainly dependent on the agricultural sectors, service sectors, and the tourism industry (Queensland Government, 2011a). In recent years, this city has experienced some extreme flood events because it is located in the vicinity of the Burnett River waterway. The Bundaberg ground elevation and the Burnett River catchment are illustrated in Figs. 3-2 and 3-3. The most recent flood responses from Bundaberg Regional Council date back to the floods in November 2010, January 2013, February 2013, and February 2015.

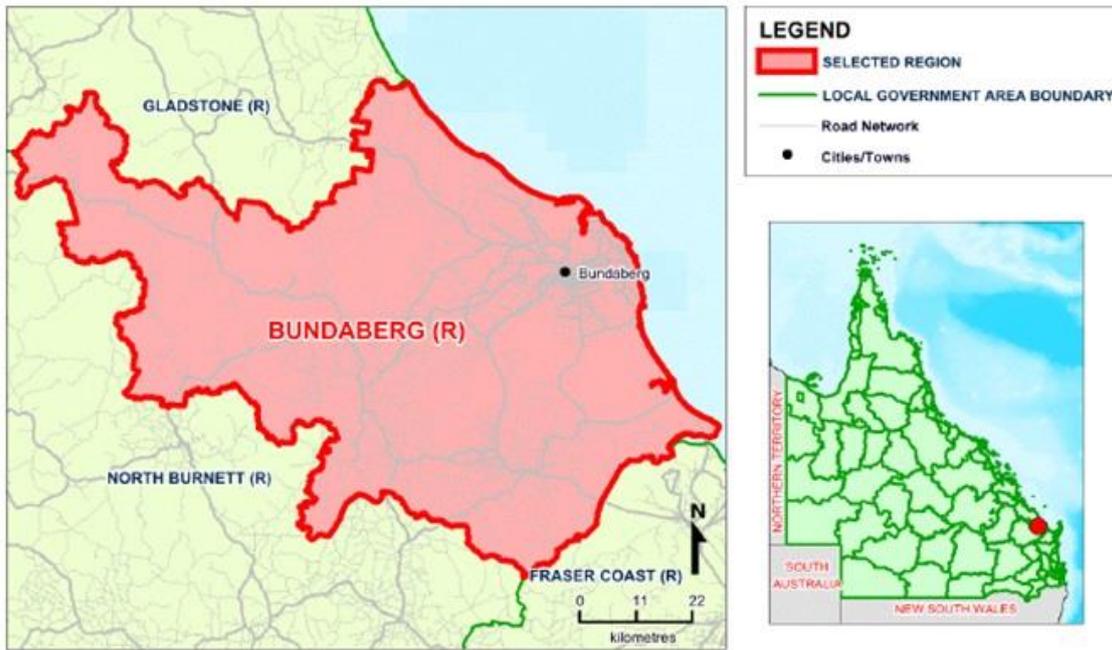


Figure 3-1: Map of Bundaberg Regional Council (Queensland Government, 2011a)

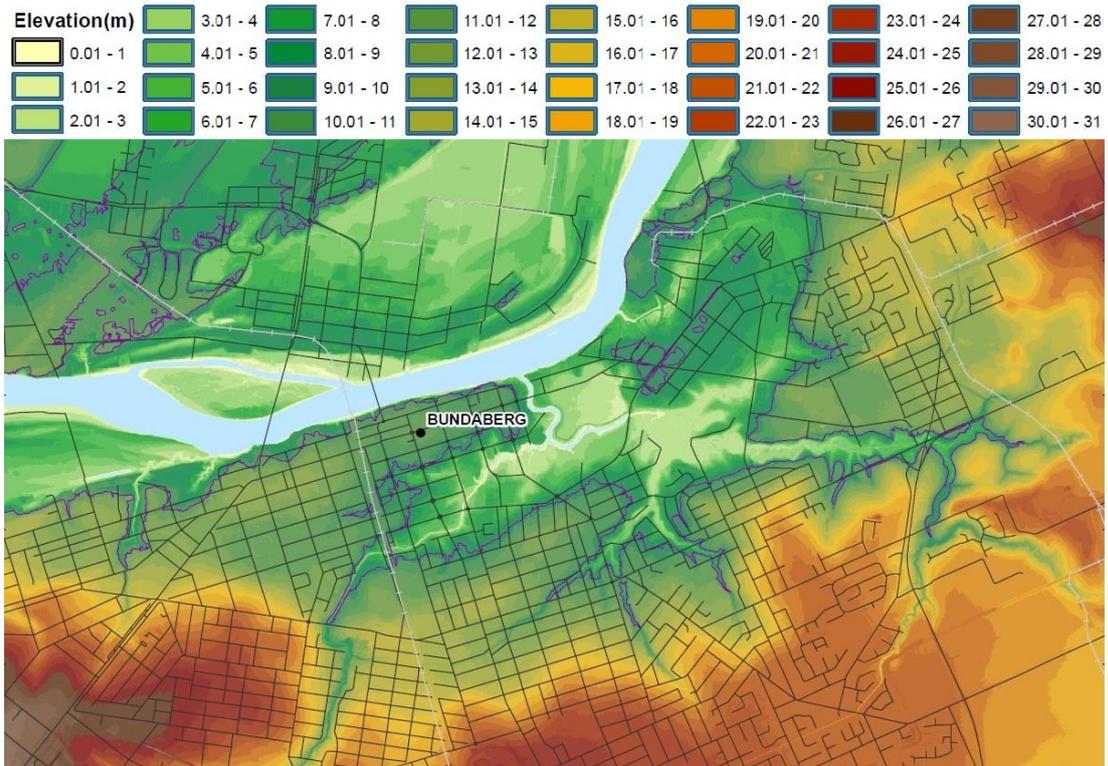


Figure 3-2: Bundaberg ground elevation (Bundaberg Regional Council, 2013a)

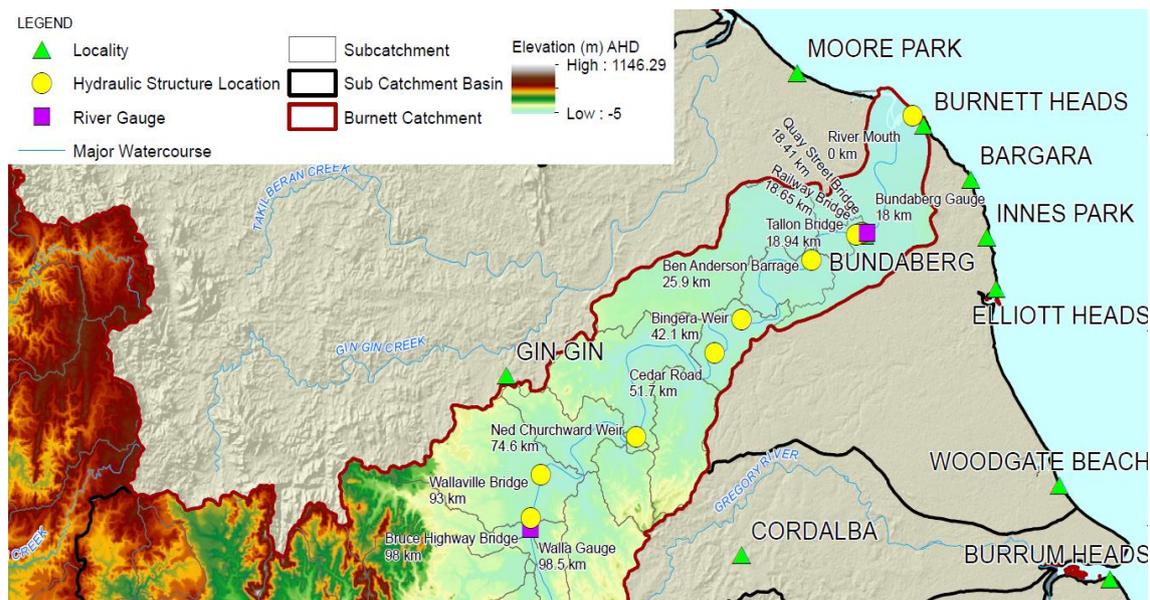


Figure 3-3: Burnett River catchment map (Bundaberg Regional Council, 2013b)

The empirical data used for calibrating FLFA_{rs} were collected after the January 2013 Bundaberg flood event. This flood event that occurred from 21 to 29 January 2013 was a result of Tropical Cyclone Oswald, and the associated rainfall and flooding had a catastrophic effect on Queensland, with it being considered as the worst flood experienced in Bundaberg's recorded history. The height of the floodwaters in Bundaberg city from Burnett River reached 9.53 metres at its peak, and over 2000 properties were affected (Queensland Government, 2013). The propagation of the water depth is illustrated in Fig. 3-4. During this flood event in the Bundaberg region, 200 businesses were inundated and over 2000 residents and 70 hospital patients were evacuated. Furthermore, the natural gas and power supplies were disrupted, agricultural and marine environments were impacted, and usage of coal and insurance claims dramatically increased (Queensland Government, 2013). In addition to this significant damage level, closures of the Bundaberg port, railways and roads had a considerable effect on the economy of this region. According to comments from the communications team of the Queensland Reconstruction Authority, Bundaberg Regional Council estimated that the public infrastructure damage from the natural disaster events of 2013 was approximately AUD 103 million.

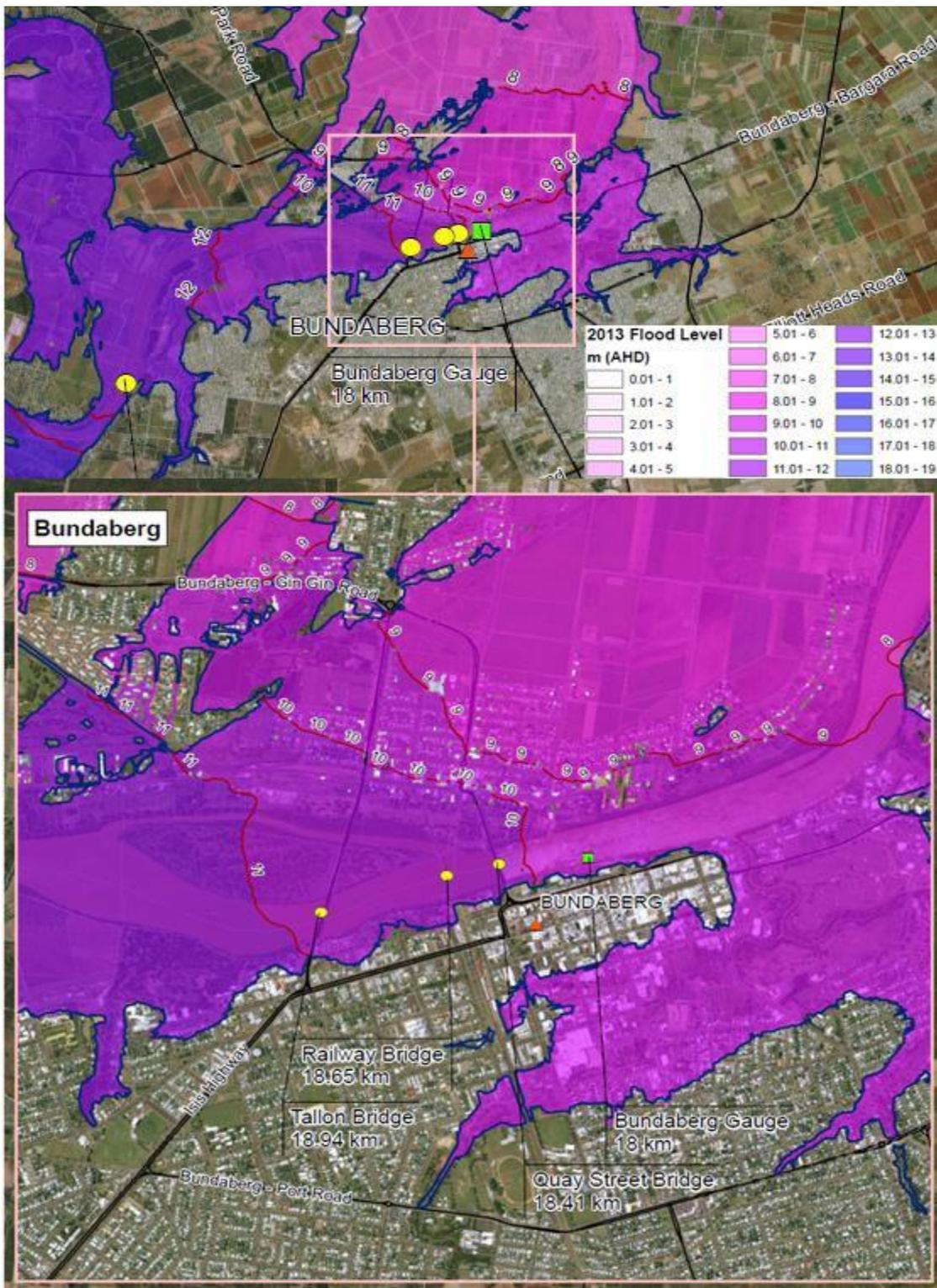


Figure 3-4: Inundation map of 2013 flood (Bundaberg Regional Council, 2013c)

Chapter 3: Calibration and Validation of FLFARs

Furthermore, for validating the applied damage models, empirical data collected from 2012 flood event in the city of Roma, located in the Maranoa region in Queensland, have been utilised. This town, as illustrated in Figs. 3-5 and 3-6, is situated on Bungil Creek, a tributary of the Condamine River. The top five industry subdivisions of employment for workers in the Maranoa Regional Council are agriculture, public administration, education, oil and gas extraction, and retail stores (Queensland Government, 2011b). According to comments from the communications team of the Queensland Reconstruction Authority, in the last few years, the Maranoa Regional Council has had to respond to the following disaster events:

- heavy rainfall and flooding in December 2014;
- the central coast and southern Queensland trough in March 2014;
- the central and southern Queensland low from 25 February to 5 March 2013;
- Tropical Cyclone Oswald and associated rainfall and flooding in 21–29 January 2013;
- Roma flooding in early February 2012;
- Roma flooding in April 2011; and
- Roma flooding in March 2010 (with a 100-year return period).

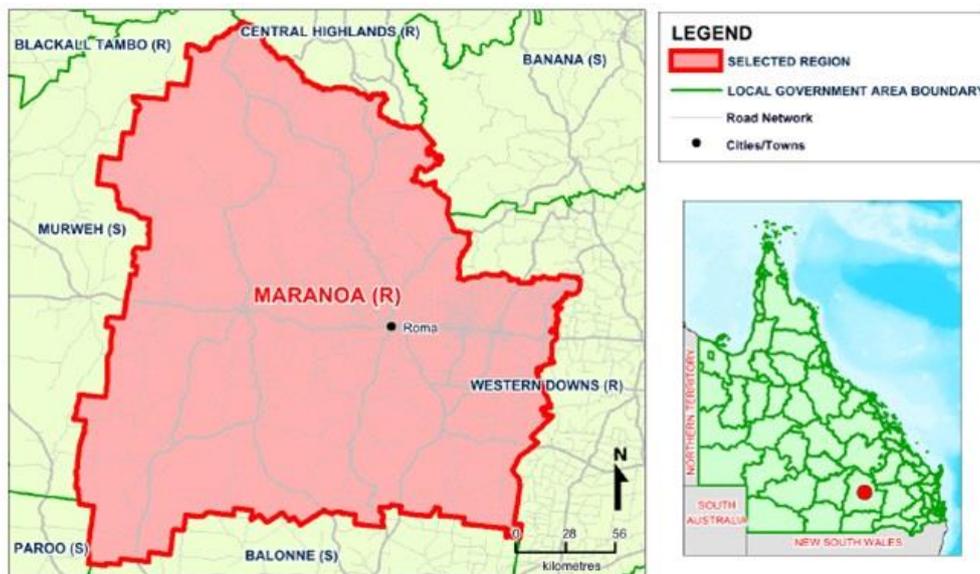


Figure 3-5: Map of Maranoa Regional Council (Queensland Government, 2011b)

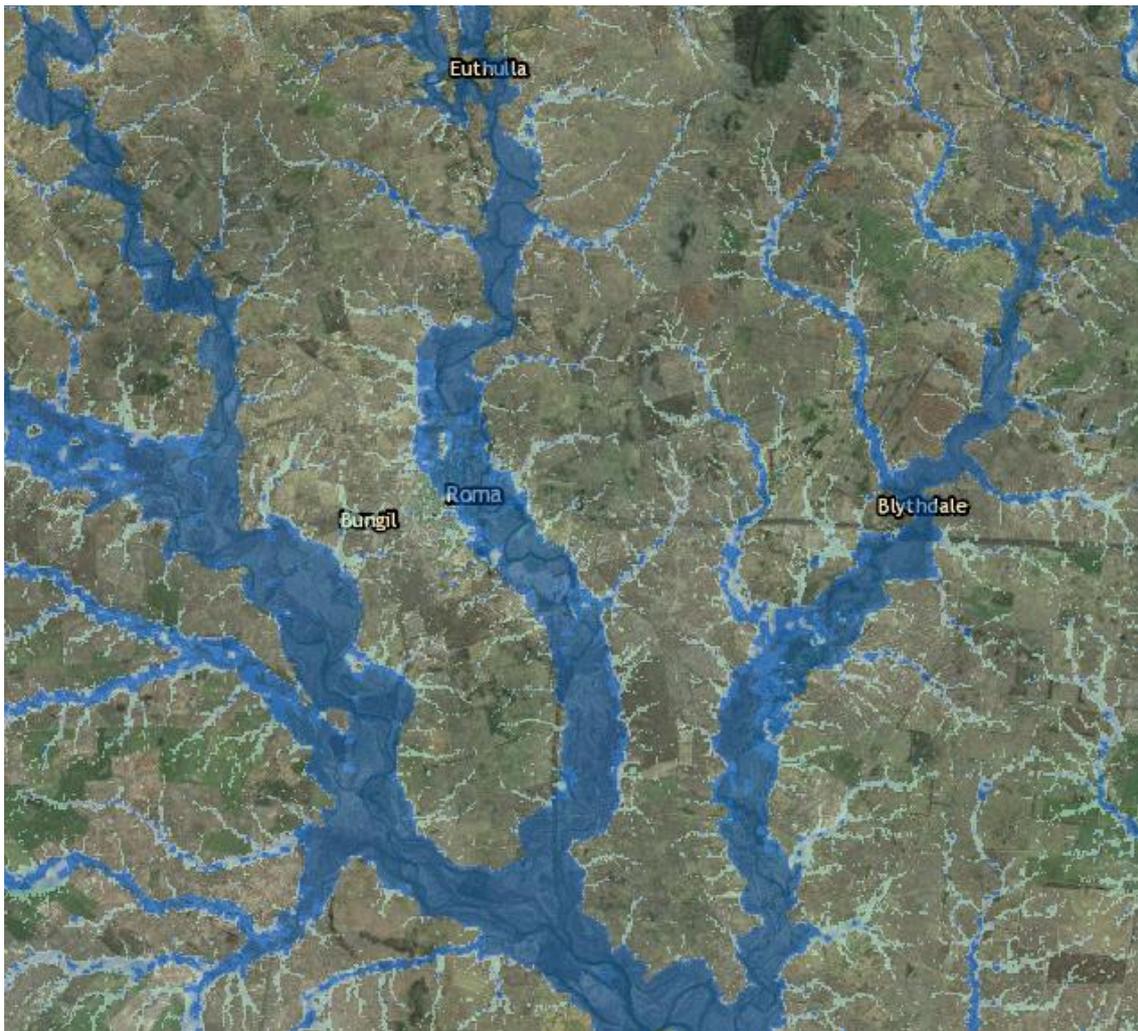


Figure 3-6: Basin-level flood modelling for Bungil Creek (Queensland Department of Natural Resources and Mines, 2015)

The flood event in 2012 is considered to be the worst flood experienced in Roma's history, having inundated 444 homes (twice as many as were flooded in 2010). The boundary of the flood is illustrated in Fig. 3-7. According to the Queensland Reconstruction Authority; the Maranoa Regional Council's estimated that the public infrastructure damage from the natural disaster events of 2012 was approximately AUD 50 million. After the 2012 flood, and having experienced three sequential years of flooding, insurance companies claimed that issuing new policies to Roma residents was only dependent on taking some new actions in regards to mitigating the risk of flood in this city.

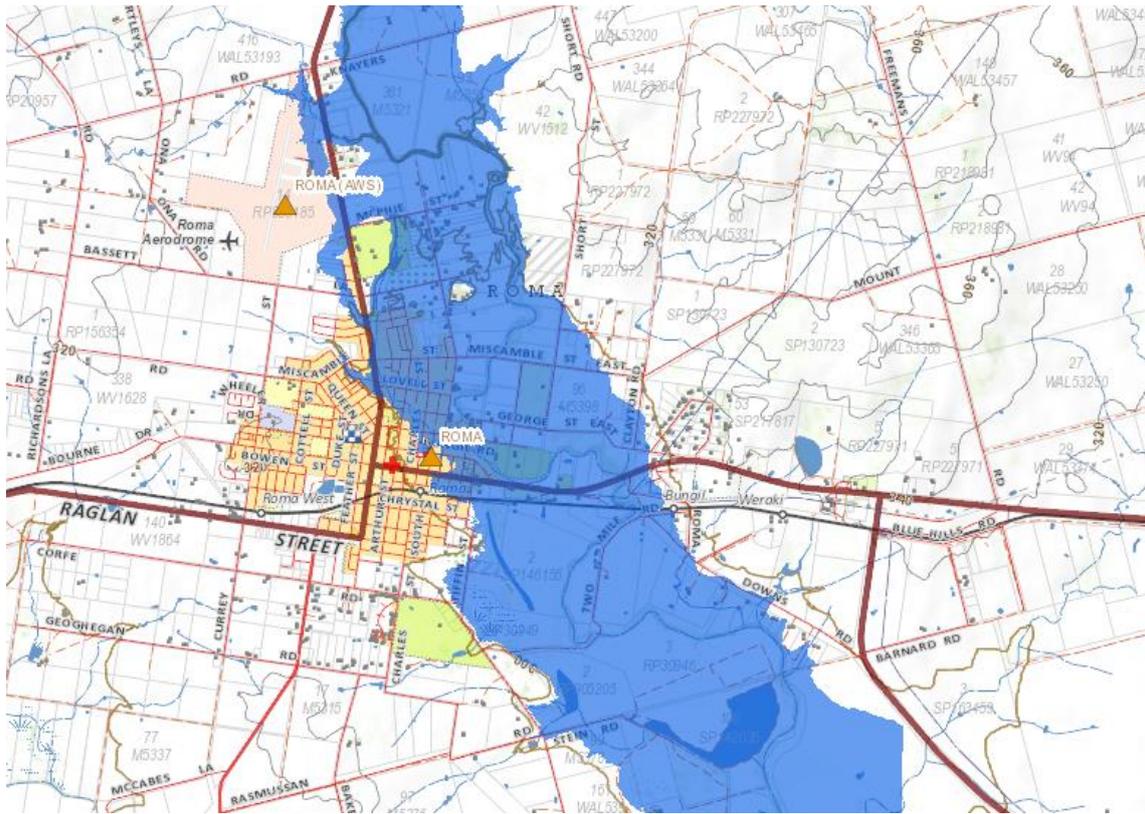


Figure 3-7: Boundary of the 2012 historic flood event (Queensland Department of Natural Resources and Mines, 2015)

3.5.2 Official Flood Loss Data

Data collection on recent extreme events is a difficult procedure, even in some developed countries such as Australia. Damage surveys after a flood are not a common activity for governments, and they mostly rely on insurance company payouts or media reports for information (Bureau of Transport Economics, 2001; McBean et al., 1986; Merz et al., 2010; Smith, 1994). Insurance companies are mainly concerned with the collection of data on repair costs and their relation to the total insured value of the flooded object. However, data sets that were gathered with the aim of classifying structural damage or deriving loss estimation models also contain information about the flood characteristics, building types, construction materials, etc. (Thieken et al., 2009). In addition to these issues regarding the standards of data gathering, these companies do

not distribute their detailed databases due to confidentiality policies. Usually, their data are only available as a total value of consequences related to one specific event. On the other hand, data released by the media are not detailed as well as insurance records and cannot be considered as official and validated resources.

Flood Loss Data of 2013

An official data set on the level of hazard, characteristics of buildings, and the magnitude of losses provided by the Queensland Reconstruction Authority were used to calibrate FLFA_{rs} developed in this study. This data set provides 592 data samples from the Bundaberg flood in 2013. After discarding the unrelated cases (buildings with irrelevant functions or characteristics), 319 final samples for the four selected building types were collected. For these samples, the impacts of flood have been presented by the depth of water above the first floor of the buildings. Furthermore, the vulnerability of the buildings has been shown by wall type (e.g. timber or brick), building use, and number of storeys.

In addition to hazard and vulnerability information, the level of structural damage has also been explained in the data set. This empirical data set, which has been collected by two post-disaster surveys, has categorised the condition of flooded buildings into undamaged, minor, moderate, severe, and total damaged rates. In addition, the guidelines of the survey describe these qualitative terms based on the affected assembly items. To be more precise, for each category of damage, it illustrates which groups of sub-assemblies (e.g. foundation, below first floor, structure, interiors and exterior walls) start to become damaged, or become partially or entirely damaged. Consequently, based on the sub-assembly approach proposed by the HAZUS technical manual (FEMA, 2012) and for exchanging the description of damages into percentage of damages, the following steps have been accomplished:

- For every type of building, the replacement value of each set of building sub-assembly compared with the total value of the building has been estimated. In that connection, the Australian construction cost guide (Rawlinsons, 2014) and cost estimation bills generated by local construction companies (e.g. Organized Builders'

cost estimation: <http://organizedbuilders.com.au/>) were utilised. Table 3-1 summarises the average contribution of sub-assembly replacement values as a percentage of the total building replacement value.

- Based on the guideline descriptions of the damaged components and the relative value of affected items compared to the entire value of the building, damage description of each building has been exchanged to one percentage of damage.
- For every building, based on the estimated percentage of damage and the reported depth of water, the percentage of damage vs. depth of water has been illustrated. Percentages of damage vs. depths of water for all samples have been depicted in Fig. 3-8.

Table 3-1: sub-Assembly replacement values for the common types of residential buildings as a percentage of the total building replacement value (an average estimation based on Rawlinsons construction cost guide (2014) and local construction companies)

Assembly components	Relative value
Foundation	9%
Below first floor	3%
Structure framing	9%
Roof covering and roof framing	7%
Exterior walls	22%
Interiors	50%
Total	100%

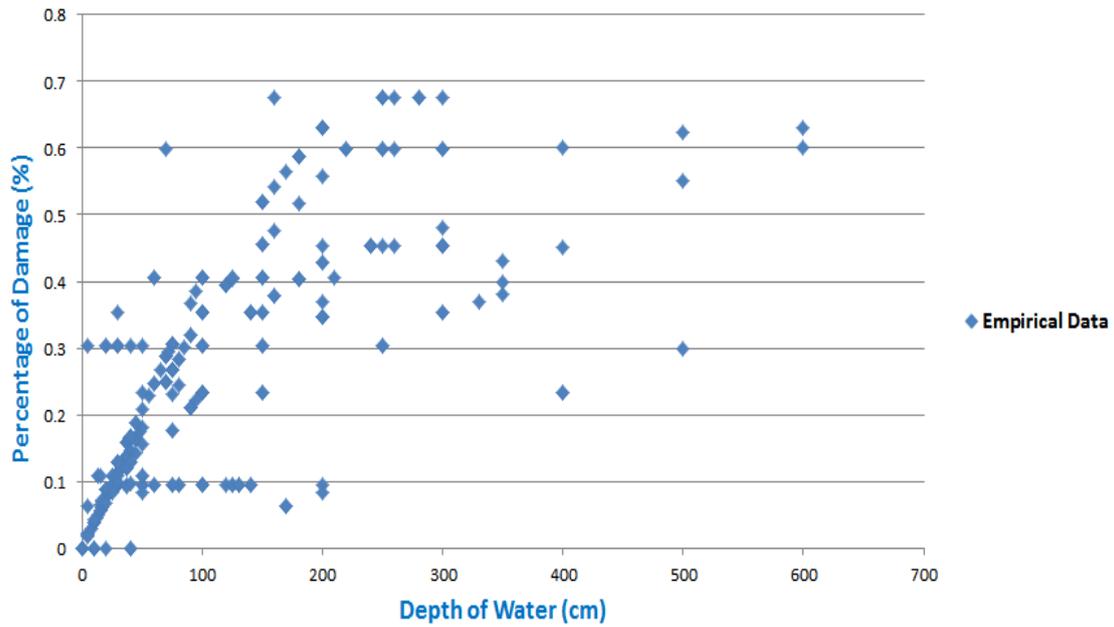


Figure 3-8: Empirical data points collected from 2013 Bundaberg flood event and utilised for calibrating FLFARs (319 samples in 4 vulnerability classes)

On the basis of sub-assembly values and guideline descriptions, Fig. 3-9 summarises the sub-assembly losses for one-storey buildings with timber walls. The vertical axis is the sub-assembly loss as a percentage of its own replacement value (extracted from the guideline descriptions), and the horizontal axis is the overall building loss as a percentage of the building replacement value (sum of the "sub-assembly losses multiplied by the average values").

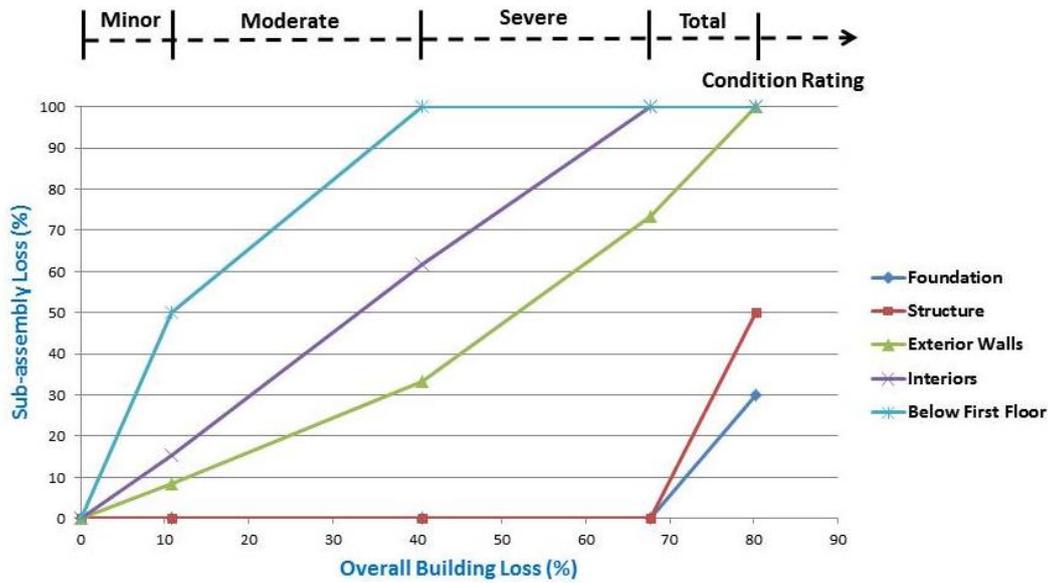


Figure 3-9: Illustration of condition rating and sub-assembly loss vs overall building loss for one-storey buildings with timber walls on the basis of 2013 empirical loss data (based on building sub-assembly approach suggested by Hazus-MH Flood Model Technical Manual, FEMA, 2012). The horizontal axis is the overall building loss as a percentage of the building replacement value, and the vertical axis is the sub-assembly loss as a percentage of its own replacement value

Flood Loss Data of 2012

To compare the performance of the applied damage models with the observed structural damages, an anonymised data set collected from the extreme event in the Maranoa region of Queensland, Australia (2012) has been utilised. This data set provides extent of damage, building type (e.g. wall type, number of storeys), and depth of water (i.e. flood level relative to first floor) for 150 inundated residential buildings (46 samples for one-storey buildings with timber walls; 14 samples for two-storey buildings with timber walls; 78 samples for one-storey buildings with brick walls; and 12 samples for two-storey buildings with brick walls). For every building, the absolute damage value has been calculated by multiplying the loss ratio by the average replacement value of each building extracted from the national exposure information system of Australia (Dunford et al., 2014). Resampling of all building loss values by means of bootstrapping was then carried out to obtain a 95 % confidence interval of the

total observed losses. This was achieved with 10,000 simulated random samples which were drawn by replacement from the structural loss values. If the total losses estimated by the selected models fall within the 95 % interval of the resampled data, their performance will be assumed to be accepted; otherwise it can be rejected. By this approach, the performance of the applied damage models in terms of structural damage estimation in the area of study will be evaluated (Cammerer et al., 2013; Seifert et al., 2010; Thielen et al., 2008).

3.6 Derivation and Calibration of FLFA_{rs} with the Flood Loss Data of 2013

Flood losses could be related to a variety factors such as lateral pressure, velocity, duration, debris, erosion, and the chemical effects of water. However, the water depth is identified as the most dominant influencing factor of flood damage to residential buildings in short-duration riverine floods (Cammerer et al., 2013; Kelman and Spence, 2004; Merz et al., 2010; Thielen et al., 2005). Therefore, in the newly derived model, only the depth of water has been considered as the main characteristics of floods.

For the newly derived model in this work (FLFA_{rs}), the extent of damage (d_h) in each stage of water (h) is a function of two different parameters: maximum percentage of damage D_{max} , which represents the total percentage of damage corresponding to the maximum depth of water (maximum height of the building relative to the first floor); and the rate control of function r . For calibrating the model, these two parameters, with reference to the empirical data should be fixed to the most appropriate values. However, due to the inherent uncertainty in the data sample, a range of estimates for the r factor and D_{max} have been provided. With this objective, this section of study has illustrated a bootstrapping approach to the empirical data to assist in describing confidence limits around the parameters of the depth-damage function. The following steps have been performed in this regard:

- Firstly, the empirical data set has been grouped into four different categories. This categorisation has been established according to considered vulnerability classes and building types.

Chapter 3: Calibration and Validation of FLFArs

- The range of maximum percentage of damage for each class of building has been selected (e.g. 60% to 80% for buildings with timber walls). This selection has been made based on the scatter of empirical data and the Geoscience Australia report (Geoscience Australia, 2012).
- For every type of building, based upon the defined range of D_{max} , different damage functions by different roots have been prepared.
- Based on the visual comparison among damage functions and the empirical data set, 210 different damage functions with the most appropriate values of r and D_{max} have been selected for each type of building. For instance, for one-storey buildings with timber walls, these 210 functions have been created by varying the r value between 1.1 and 2, and D_{max} between 60% and 80%.
- Subsequently, resampling of empirical loss values by means of bootstrapping was carried out; with the help of chi-square test of goodness of fit, the best-fitted values of r and D_{max} were extracted.
- Resampling of building loss values was continued up to 1000 times, and for each bootstrap the previous stage and goodness-of-fit test was performed. By this iteration, the average of fitted values of r and D_{max} converged to the optimal values used for the most-likely function. Also, the range of D_{max} and r parameters, which were used for generating the maximum and minimum functions, was extracted from the population of fitted values.

The range of estimates we are portraying with the D_{max} and r values express the lack of confidence in the damage-depth samples in representing the true uncertainty that exists in the population. Due to the fact that the relationship between flood impacts and losses to buildings is related to the characteristics of buildings (Cammerer et al., 2013; Thielen et al., 2005), these steps have to be repeated for all vulnerability classes and buildings types. Results of the model calibration are summarised in Tables 3-2 and 3-3. Furthermore, the final damage functions have been depicted in Figs. 3-10 and 3-11.

Table 3-2: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test for one-storey buildings

One-storey buildings					
Wall type	Number of samples	Parameters	Range of parameters		
			Minimum	Most-likely	Maximum
Timber	89	r	1.3	1.55	2
		D _{max}	64%	70%	74%
Brick	143	r	1.2	1.45	1.9
		D _{max}	54%	60%	65%

Table 3-3: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test for two-storey buildings

Note: Subscripts of "r" and Dmax parameters represent the floor number.

Two-storey buildings					
Wall type	Number of samples	Parameters	Range of parameters		
			Minimum	Most-likely	Maximum
Timber	49	r ₁	1.5	2.3	2.4
		r ₂	1.3	1.5	1.55
		D _{max1}	38%	42%	43%
		D _{max2}	25%	28%	28%
Brick	38	r ₁	1.4	2	2.3
		r ₂	1.2	1.4	1.5
		D _{max1}	32.5%	34%	36%
		D _{max2}	25.5%	26%	28%

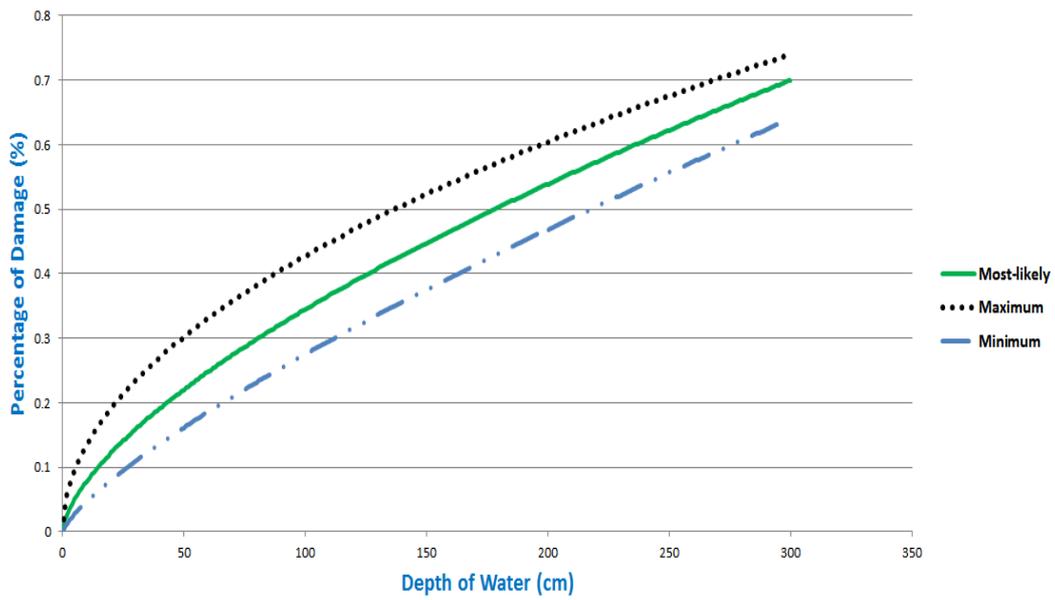


Figure 3-10: Visualization of minimum, most-likely and maximum damage functions, calculated by bootstrap and chi-square test, for one-storey buildings with timber wall

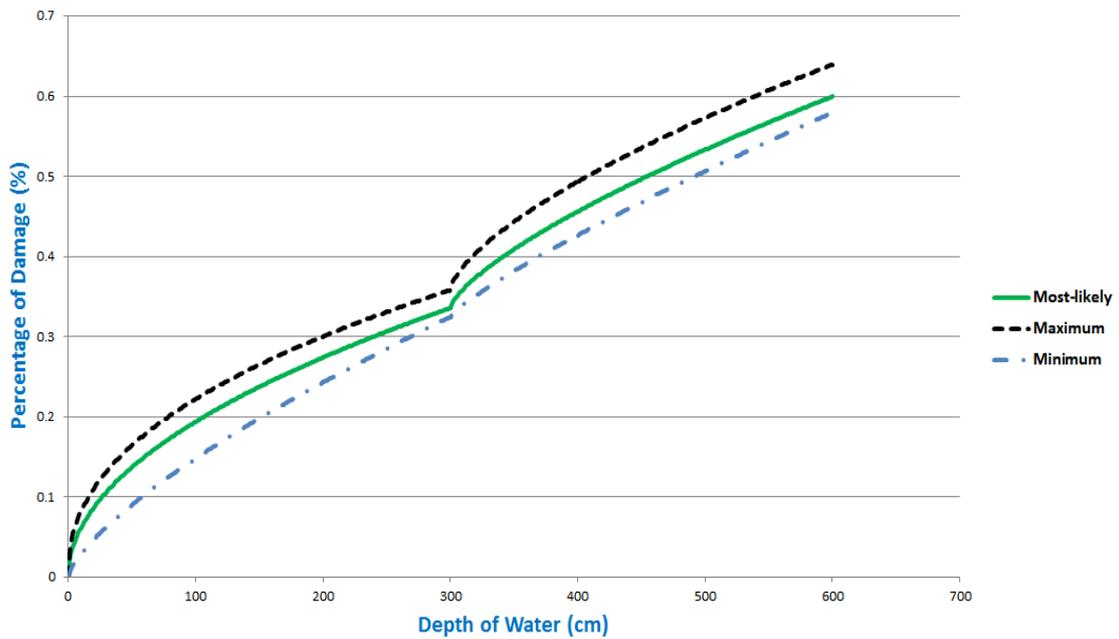


Figure 3-11: Visualization of minimum, most-likely and maximum damage functions, calculated by bootstrap and chi-square test, for two-storey buildings with brick wall

As can be seen from Table 3-3, for two-storey buildings, due to the different distribution and value of components in the height of the first floors in contrast to the second floors, different values should also be considered for the r and D_{max} factor of each storey. Referring to the higher rate of damage in the first floor of buildings compared to the second floor, the value of r in the first storey of buildings is expected to be more as well. This assumption is also reflected by statistical analysis. Although it would be more economical to replace a building that has more than 60 % damage rather than repair it (Nadal et al., 2010; Scawthorn et al., 2006), these damage curves have been extended up to the maximum value of damages for a better comparison with other models in the next part of this study.

3.7 Models Comparison

3.7.1 Applied Damage Models

As mentioned earlier, since relative damage curves are more flexible in terms of transferability to a new area (Cammerer et al., 2013; Merz et al., 2010), besides FLFA_{rs}, two more relative damage models have been selected for comparison in this study.

Geoscience Australia (GA) Depth-Damage Function

Some generic depth-damage curves for south-east Queensland have been presented in the report by Geoscience Australia (Geoscience Australia, 2012). These synthetic curves are prepared for estimating the magnitude of damage for building fabrics (including interiors) and building contents (including belongings that may be removed from the house) separately. Moreover, this report represents different curves for different vulnerability classes and building types based on the size of buildings, construction materials, the presence of garages, and the number of storeys (Geoscience Australia, 2012). It is worth noting that the performance of these synthetic damage curves has not been calibrated with any related empirical data sets. However, these damage curves are good examples for comparison for the following reasons: they express the magnitude of

damages relatively; they are prepared by Geoscience Australia for use in our area of study; and they are prepared by the synthetic logic approach.

By taking the depth of water as the hydraulic input, this model gives the percentage of damage for every type of building separately. From this report, and with the aim of result comparison, four damage curves that are more related to the building types of this study have been selected.

FEMA/USACE Depth-Damage Function

The United States Federal Emergency Management Agency (FEMA) and Army Corps of Engineers (USACE) provide stage-damage curves for flood damage estimation of residential buildings. The functions are “relative” and damages are expressed as a percentage of total building value (USACE, 2003). Models are provided for one-storey or multi-storey buildings, with and without basements. Also, they represent the percentage of damage for the building’s structure and contents separately (Comiskey, 2005). It is worth mentioning that similar to the GA approach, the structural curves cover all building fabrics, including interiors. Due to the frequent usage of the USACE model in Australia, this relative damage function has been selected for comparison in this study.

Similar to the other models, the only hydraulic input of these curves would be the depth of water. Also, the vulnerability classes considered in this method are related to the number of storeys and presence of a basement. From the provided curves by USACE, damage curves related to one-storey and two-storey buildings without a basement are the most appropriate and relevant curves for this study.

Visual comparisons of the depth-damage functions provided by the three methodologies are shown in Figs. 3-12 and 3-13.

Chapter 3: Calibration and Validation of FLFARs

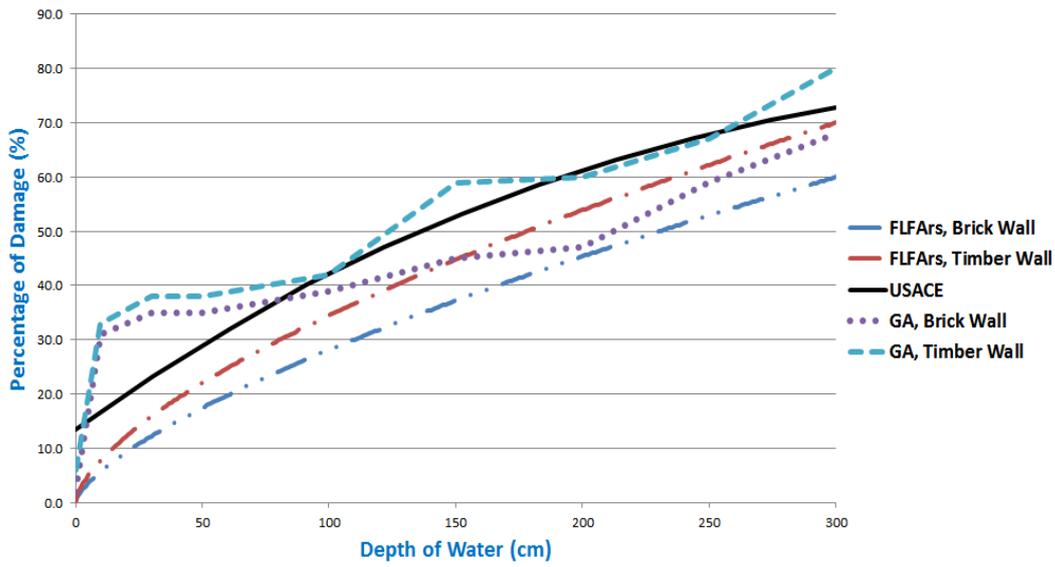


Figure 3-12: Model comparison for one-storey buildings (the FLFARs has been derived by the most-likely functional parameters)

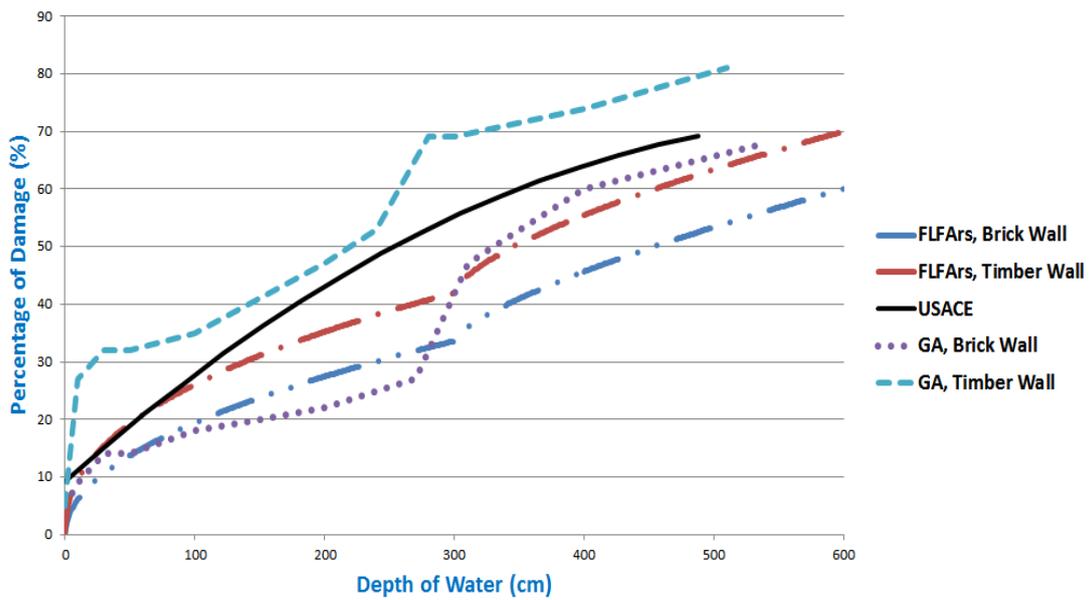


Figure 3-13: Model comparisons for two-storey buildings (the FLFARs has been derived by the most-likely functional parameters)

3.7.2 Results Comparison and Model Validation for the Maranoa Study Area

Results of applied damage models have been compared with the observed loss data collected from 2012 Maranoa flood event. As stated before, in addition to FLFA_{rs} that has been calibrated with the damage data from the Bundaberg region, two more models (one local and one from the USA) have been derived.

The overall reported loss for the 150 cases (building fabric) affected by the Maranoa flood amounted to AUD 13.17 million (mean of the 10,000 bootstrap samples), and the 95 % confidence interval ranges from AUD 13.03 million to AUD 13.32 million. As mentioned previously, if the estimated total losses by the selected models fall within the 95 % interval of the resampled data, their performance will be assumed to be accepted and sufficiently accurate; otherwise it is rejected (Cammerer et al., 2013; Seifert et al., 2010; Thieken et al., 2008). It is worth mentioning that for estimating the absolute value of damages for each building, the loss ratios extracted from the damage models have been multiplied by the same replacement values used in section 4.2.2.

The performance of all flood loss models used to estimate the total building damage of the 2012 event is summarised in Table 3-4. It can be observed that the result of FLFA_{rs} with the most-likely functional parameters lie within the confidence interval, and its performance may be acceptable. However, results of the GA and USACE models do not lie within the confidence interval of the reported loss and their performance is rejected in this area of study. This issue and the validation procedure illustrates the importance of model calibration with the empirical local data sets, particularly when the water depth is the only hydraulic factor considered (Cammerer et al., 2013; Chang et al., 2008; McBean et al., 1986).

Table 3-4: Comparison of different loss estimates with the observed flood damage (95% confidence interval) on residential building structures for the flood event of February 2012. Note: for model validation, FLFA_{rs} has been derived by the most-likely functional parameters.

Damage Function	Estimated Losses (in AUD million)	
FLFA _{rs}	13.09	
GA Model	25.42	
USACE Model	20.21	
Reported Loss in 2012	AUD 13.03 million (2.5 th percentile)	AUD 13.32 million (97.5 th percentile)

Furthermore, errors in the estimates from the aforementioned models have been evaluated by the mean bias errors (MBE); the mean absolute error (MAE); and the root mean square error (RMSE) statistical tests. The MBE provides the average deviation of the estimated ratios from the observed ratios, and describes the direction of the error bias. A negative MBE indicates an underestimation in the estimated ratios, while a positive value shows an overestimation. The MAE represents the average absolute deviation of the estimated ratios from the observed values and is a quantity used to measure how close the estimates are to the empirical data. The RMSE also expressed the variation of the estimated ratios from the observed ratios and it signifies the standard deviation of the differences between the estimated ratios and observed values (Chai and Draxler, 2014; Seifert et al., 2010). By these statistical comparisons, the performance of the derived models equated with the empirical data set has been assessed, and the results are summarised and compared in Table 3-5.

Table 3-5: Numerical comparison and error statistics of depth-damage function performance for the flood event of February 2012 (MBE: mean bias error; MAE: mean absolute error; RMSE: root mean squared error)

	FLFA _{rs}	GA method	USACE method
MBE	-0.001	0.167	0.096
MAE	0.03	0.17	0.10
RMSE	0.04	0.19	0.11

This table clearly shows that FLFA_{rs} has a better performance compared to other models. The MBE value shows a slight bias, very close to zero, for the newly derived model (FLFA_{rs}), while this value for the other methodologies indicates a larger average deviation from the observed losses. On the other hand, the MAE and the RMSE for FLFA_{rs} estimates are 3 and 4 %, respectively. However, other models have larger average values of absolute deviation and greater values of standard deviation. This matter signifies a higher variation in the errors of the GA and USACE models estimates. As summarised in Fig. 3-14, the individual differences between the estimated ratios and observed values (residuals) in FLFA_{rs}, in contrast to other methodologies, have less magnitude and variation. The FLFA_{rs} clearly achieves better results than the models which are not calibrated with the local damage data.

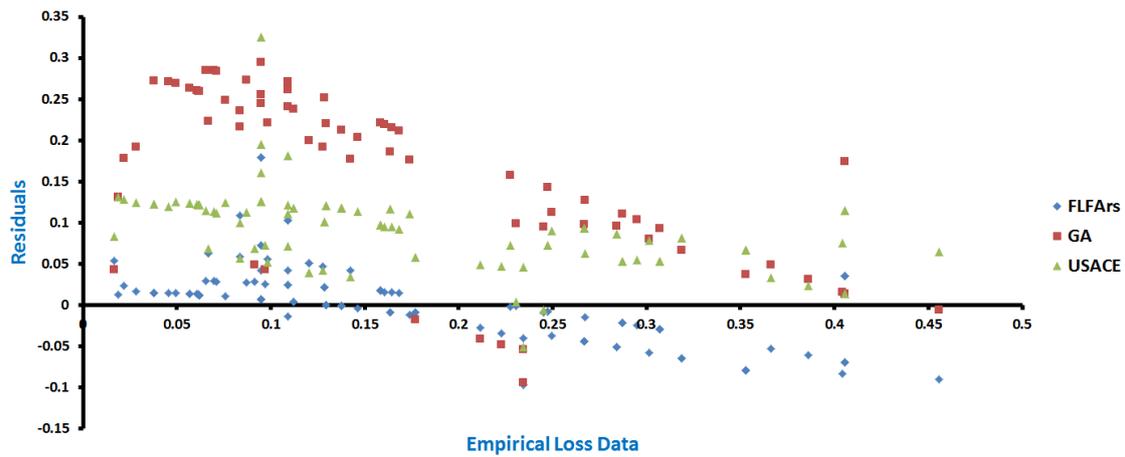


Figure 3-14: Residual plot used for comparing the performance of selected damage functions relative to empirical loss ratios

3.8 Conclusions

Damage mitigation and consequence reduction in terms of lessening the probability of expected losses is the main focus of risk management. While much effort has gone into emergency management in Australia, flood damage assessment is still crude and affected by large uncertainties. Stage damage curves are the most common and internationally accepted methods for flood damage estimation. Despite the simplicity of using these curves for different water depths, non-calibrated curves could considerably raise the level of uncertainty in flood damage assessment. Due to a lack of empirical data from recent extreme events, few studies have been conducted to explore the validation of well-known overseas methodologies in Australia. Also, most of the synthetic methodologies prepared for Australia are not calibrated with empirical loss data or express the magnitude of damage in absolute monetary values. These types of curves are not flexible for transferring in spatial scale or time, and their results are not reliable unless they have been calibrated with the conditions of the new region of study.

The focus of this study is on direct, tangible damages of four common types of residential buildings. This study aimed to present a new flood loss function for Australian residential structures (FLFAR_{rs}). The new function is a general methodology

for describing the magnitude of damage for each stage of water, and suggests some simple and flexible curves with regards to the variability in characteristics of buildings. The FLFA_{rs} has been calibrated according to the geographical conditions in the area of study (i.e. building characteristics and flood specifications) using empirical data sets collected from the 2013 flood event in the Bundaberg region of Queensland, Australia. Finally, a statistical comparison for estimating the level of reliability and contrasting the performance of the methodology with damage data collected from the 2012 Maranoa flood event was conducted. With this objective and in addition to FLFA_{rs}, a well-known overseas methodology and a local state approach were used for the area of study.

The analysis reveals that the results of the flood damage models are strongly dependent on the selected stage-damage curves and flood damage estimation without model calibration might result in inaccurate values of losses. Therefore, it is very important to be aware of associated uncertainties in flood risk assessment if the loss functions have not been calibrated with the conditions of the region of study. The results of this study show that even the state methodologies might considerably overestimate the magnitude of flood impacts, or significantly underestimate the value of losses if they have not been calibrated with the empirical loss data.

Acknowledgements

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Chapter 3: Calibration and Validation of FLFArs

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4 DEVELOPMENT AND EVALUATION OF FLFA_{CS}

A NEW FLOOD LOSS FUNCTION FOR AUSTRALIAN COMMERCIAL STRUCTURES [Published Chapter]²

4.1 Abstract

Commercial building flood losses significantly affect the Australian economy; however, there are not many models for commercial flood damage estimation and their results are not reliable. This study has attempted to derive and develop a new model (FLFA_{CS}) for estimating the magnitude of direct damage on commercial structures. The FLFA_{CS} - Flood Loss Function for Australian commercial structures, was calibrated using empirical data collected from the 2013 flood in Bundaberg, Australia, and considering the inherent uncertainty in the data sample. In addition, the newly derived model has been validated using a K-fold cross-validation procedure. The model performance has also been compared with the Flood Loss Estimation MOdel for the commercial sector (FLEMO_{CS}) and the Federal Emergency Management Agency (FEMA) damage functions from overseas, as well as the ANUFLOOD damage model from Australia. The validation procedure shows very good results for FLFA_{CS} performance (no bias and

² Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016. Development and evaluation of FLFA_{CS} – A new Flood Loss Function for Australian commercial structures. *Int. J. Disaster Risk Reduction*, 17, 13-23

only five per cent mean absolute error). It also shows that ANUFLOOD, as Australia's most prevalently used commercial loss estimation model, is still subject to very high uncertainty. Hence, there is an immediate need for a project to build new depth-damage functions for commercial and industrial properties. Awareness of these issues is important for strategic decision-making in flood risk reduction and it could amplify the cognition of decision-makers and insurance companies about flood risk assessment in Australia.

4.2 Introduction

Statistical analyses shows the considerable impacts of flood risk compared to other types of natural hazards (André et al., 2013; Kourgialas and Karatzas, 2012; Llasat et al., 2014; UNISDR, 2009). In Australia, floods are the most costly of all disaster types, contributing 29 % of the total cost for the nation's economy and the built environment (Bureau of Transport Economics, 2001; Khalili et al., 2015). Unfortunately, unsustainable developments and global warming are increasing the risk of flood (Elmer et al., 2012; Kundzewicz et al., 2005; McGrath et al., 2015). Consequently, flood risk assessment and flood risk mitigation are gaining more attention (André et al., 2013; Kreibich et al., 2010; Othman et al., 2014).

Flood risk can be defined as the probability and magnitude of expected losses (André et al., 2013; Elmer et al., 2010; Kaplan and Garrick, 1981; Kreibich et al., 2010; Mouri et al., 2013; Neale and Weir, 2015; UNISDR, 2004). Therefore, loss estimation and consequence assessment is an indispensable part of flood risk assessment, and the results will provide decision-makers with an essential tool for planning better risk reduction strategies (Emanuelsson et al., 2014; Gissing and Blong, 2004; McGrath et al., 2015; Merz et al., 2010).

In general, flood losses can be categorised into direct or indirect (Meyer et al., 2013; Molinari et al., 2014a; Thielen et al., 2005); and marketable (tangible) or non-marketable (intangible) values (André et al., 2013; Kreibich et al., 2010; Molinari et al., 2014a). Direct damages take place due to physical contact between the floodwater and

inundated structures (Hasanzadeh Nafari et al., 2016; McGrath et al., 2015; Morrison and Mollino, 2012). This study is limited to direct, tangible damages of commercial structures due to a short duration of riverine (low velocity) inundation.

In Australia, direct tangible damages of commercial buildings could be estimated by the Rapid Appraisal Method (RAM) or by function approaches (e.g. ANUFLOOD). Function approaches are the most common and internationally accepted methodology (Hasanzadeh Nafari et al., 2016). They make a causal relationship between the magnitude of the hazard and resistance of flooded objects, and can estimate the extent of losses for each stage of water (Dewals et al., 2008; Grahn and Nyberg, 2014; Jongman et al., 2012; Kreibich and Thielen, 2008; Molinari et al., 2014b; Smith, 1994; Thielen et al., 2006). Function approaches can be categorised into absolute and relative types. Absolute functions express the magnitude of damages in monetary values; while relative types estimate the dimension of losses as a ratio of the total value, i.e. replacement value or depreciated value (Kreibich et al., 2010). Relative loss functions in contrast to absolute loss functions have better transferability in space and time since they are independent of changes in market values (Merz et al., 2010). However, both types are restricted to the area of origin in terms of geographical conditions, i.e. building characteristics and flood specifications (Cammerer et al., 2013; McGrath et al., 2015; Proverbs and Soetanto, 2004). Therefore, the results of transferred models contain a high level of uncertainty if they have not been calibrated with the empirical data sets collected from the new region of study (Cammerer et al., 2013; Molinari et al., 2014b).

Commercial sector flood losses significantly contribute to the economy and to societal welfare. Hence, any disruptions in their activities due to direct damages might cause indirect and induced long-term losses (Haque and Jahan, 2015; Haraguchi and Lall, 2014). Also, inaccurate loss estimation for commercial buildings leads to wasted effort, money and resources for insurance companies and organisations involved in risk mitigation (McBean et al., 1986; McGrath et al., 2015). In spite of these facts, available approaches have concentrated on residential building losses, and they are still subjected

to a considerable level of uncertainty for commercial building flood loss estimation (Gissing and Blong, 2004; Kreibich et al., 2010).

This study has derived a new Flood Loss Function for Australian commercial structures (FLFA_{cs}). The newly derived model is a general methodology for swiftly describing the extent of losses for each level of flood, and suggests a simple and flexible curve with regards to the variability in characteristics of structures. The FLFA_{cs} has been calibrated for Australian geographical conditions by using an empirical data set collected from the 2013 flood in Bundaberg, Queensland, Australia. Uncertainties pertaining to the newly derived function have been considered as well. In addition, performance of this function has been compared with an Australian methodology as well as two well-known overseas methodologies. Accordingly, the accuracy and validation of each model compared to the empirical data set has been evaluated and examined.

On the whole, the results of flood damage models provide the input data for subsequent damage reduction, vulnerability mitigation and Disaster Risk Reduction (DRR). Therefore, it is very important to be aware of associated uncertainties.

4.3 Background

In Australia, RAM and ANUFLOOD are the most common models for the estimation of direct losses of commercial structures. The RAM, developed by Sturgess and Associates (2000), considers some mean values of damage for all flooded buildings, including those inundated above and below floor level, and estimates the magnitude of potential losses. Potential losses are the maximum possible value of losses without considering any mitigation measures (Bureau of Transport Economics, 2001; Hasanzadeh Nafari et al., 2016; Molinari, 2011; Molinari et al., 2013). This methodology allocates a damage value of AUD20,500 to inundated businesses less than 1000 m² in size, and some individual damage values (in dollars per square metre) for businesses larger than 1000 m² in size (Gissing and Blong, 2004; Sturgess and Associates, 2000). The value of estimated damages includes losses to building

structures and contents (Kreibich et al., 2010) and could be converted to actual values by using some ratios, suggested based on the previous flood experiences and early warning time (Gissing and Blong, 2004; Molinari, 2011; Sturgess and Associates, 2000).

Although this methodology for initial rapid assessment is useful and inexpensive, the results are considerably inaccurate and uncertain (Barton et al., 2003; Gissing and Blong, 2004). In addition, this averaging method has not precisely considered the variability of commercial buildings with regard to building characteristics, building materials, and building exposure values (Handmer et al., 2002). Also, propagation of water depth and different magnitudes of flood impacts have been neglected in this approach. Consequently, this model only calculates an accumulated value of the total damages occurred, without considering its distribution over the inundated area. It is also noted that due to economic inflation, the potential damage values of the RAM methodology need regular recalibration. Under other circumstances, this method might underestimate the value of losses considerably (Merz et al., 2010). Furthermore, because RAM does not separate the magnitude of structural damage from contents losses, the conversion of potential damage to actual damage, due to the different nature of movable inventories from non-movable components with lead-time, is problematic (Gissing and Blong, 2004).

In addition to the averaging method, stage-damage curves can be used for the estimation of flood losses in commercial sectors. These models estimate the magnitude of losses for different stages of flooding, and the magnitude of damage increases by over-floor water depth increments (Gissing and Blong, 2004). Stage damage curves have been grouped into two different main classifications: empirical and synthetic curves (McBean et al., 1986). Empirical curves build on surveyed damage data. The estimated results are more accurate due to taking into account the effect of mitigation measures and the variability within one category of building (Kreibich et al., 2005; Merz et al., 2010, 2004). However, Smith (1994) discussed that by moving in time and space, mitigation measures, level of preparedness, characteristics of floods, and the

attributes of buildings, could alter significantly. Therefore, gathering data from one flood event and using it as a guide for future events prediction, even in the area of origin, requires a complicated process of extrapolation (Gissing and Blong, 2004; McBean et al., 1986; Smith, 1994). As a solution, synthetic curves based on a valuation survey have been created for different types of buildings. Valuation surveys direct attention to the value and level of all components that are situated above the basement (Barton et al., 2003). The extent of potential losses for different stages of flood via “what-if” questions is estimated based on the distribution of components in the height of the building and the degree of fragility of each item (Gissing and Blong, 2004; Merz et al., 2010). In addition to the advantages related to a high degree of standardisation and independency from historic data, a valuation survey, even for one type of building, needs a high level of effort. Also, due to estimating the extent of potential losses, this approach does not take into account the effects of mitigation measures (Hasanzadeh Nafari et al., 2016; Merz et al., 2010; Smith, 1994).

ANUFLOOD commercial damage curves (Smith, 1994) are empirical damage functions that are used commonly in Australia. This methodology expresses the magnitude of losses as a total value including damage to the structure and inventories. Furthermore, this model has presented different depth-damage functions based on the size of the business (i.e. smaller than 186 m², between 186 m² and 650 m², and larger than 650 m²) and value of buildings (i.e. depends on the vulnerability of contents). The same as RAM, damage for small- and medium-sized classes have been given in absolute values; while for large-sized classes, it has been presented in dollars per square metre (Gissing and Blong, 2004).

Similar to most Australian approaches, this approach expresses the magnitude of damage in absolute fiscal values. As stated earlier, these types of functions, in contrast to relative loss functions, are more rigid for transferring in space or time (Merz et al., 2010). For instance, the RAM report demands that the magnitude of damage estimated by the ANUFLOOD method should be increased by 60 % and its performance is no longer sufficiently accurate (Sargent, 2013; Sturgess and Associates, 2000). The reason

for this is related to the fact that these curves are based primarily on a 1986 flood event in Sydney and they need updating due to changes in the value of the dollar compared to today's value. Hence, their results are not reliable unless they have been recalibrated frequently (Merz et al., 2010).

To address these issues, the authors have attempted to develop a new empirical-synthetic model with a better level of accuracy in results and transferability in time and space compared to the available Australian methodologies. Also, this new model is easy enough to understand and generalise for other types of structures and vulnerability classes. Despite the fact that the itemised estimation survey proposed for synthetic damage functions seems a little confusing and takes a long time (Merz et al., 2010), the new model for evaluating the assembly components and tracking the vertical parameters, by considering more general categories, has tried to simplify the process as much as possible.

4.4 The newly derived function (FLFA_{cs})

For developing an analytical stage damage curve in one area of study, a representative building category is first needed. Next, for the representative classification, an average distribution of the building components in the height of the structure should be taken out. Eventually, the percentage of damage for every stage of water could be estimated based on the average value of fragile items relative to the total value of the structure (Bureau of Transport Economics, 2001). In this study and for developing the newly derived model, these steps have been put well to use.

Firstly, selection of the representative group and the vulnerability class has been made based on the characteristics of existing structures (e.g. material, size and age) collected from the national exposure information system of Australia (Dunford et al., 2014). This data set shows that 70 % of commercial buildings in our areas of study are one-storey buildings with masonry walls and slab-on-ground. Also, these buildings are used for retail trades, repair or personal services, or professional offices; and their size,

on average, is 400 m². In addition, 75 % of these buildings have been constructed before 1980.

Next, for resolving the stated issues related to the significant efforts required for data gathering and details surveying, some more generic sub-assembly groups have been defined. To be more specific, components of commercial structures based on the sub-assembly approach proposed by the HAZUS technical manual (FEMA, 2012) have been grouped into five main categories, as

- Foundation and below first floor
- Structure framing
- Roof covering and roof framing
- Exterior walls: includes wall coverings, windows, exterior doors and insulation
- Interiors: includes interior walls and floor framing, drywall, paint, interior trims, floor coverings, cabinets, and mechanical and electrical facilities.

The percentage of damage for every stage of water is a function of fragility and value of flooded categories. Therefore, for pursuing the real behaviour of each category against the impacts of water, and resolving the issue related to ignoring the effect of mitigation measures in synthetic methods (Merz et al., 2010), the shape of the newly derived function has been adjusted and calibrated using a historic data set collected from a recent extreme event. Hence, this approach could be named as an empirical-synthetic model.

The FLFAcs has been built on a general methodology which attempts to generate a simple and flexible curve to depict the extent of flood losses for every stage of water quickly. The proposed formula can create a flexible curve with regards to variability in the number of storeys, height of storeys, and the distribution of assembly items through the height of the building. Therefore, users can manipulate and calibrate this model easily based on the characteristics, uses and types of structures.

This methodology has been developed by considering the variability of structural components, namely flood vulnerability and exposed value. More specifically, the

vulnerabilities of structural components are different from each other, and each assembly category starts damaging after a specific level of total damage and subsequent to different water depths. Also, the exposed value of each category relative to the total value of the structure is different, and the most valuable items (e.g. the interiors and the exterior walls) start damaging from the first few centimetres of water depth (FEMA, 2012). This means that the rate of damage in the first stages of flooding is greater than the remaining stages. Therefore, the slopes of the damage curves might vary based on an exponential equation (Cammerer et al., 2013; Elmer et al., 2010; Hasanzadeh Nafari et al., 2016; Kreibich and Thielen, 2008).

The power (r) of Equation (1) controls the rate of alteration in the percentage of damage relative to the growth of water depth. In general, a higher value for " r " means a faster rate of damage at the first few metres of building height (Hasanzadeh Nafari et al., 2016). The general formula has been proposed as shown below:

$$d_{hi} = \left(\frac{h_i}{H_i} \right)^{\frac{1}{r_i}} \times D_{\max i} \quad (1)$$

where h_i = the depth of water above the i_{th} floor, d_{hi} = the percentage of damage corresponding to the depth of water above the i_{th} floor, H_i = the maximum height of i_{th} floor, $D_{\max i}$ = the maximum percentage of damage for the i_{th} floor corresponding to the maximum height of i_{th} floor, and r_i = the rate control for the i_{th} floor (i.e. for the representative group of buildings in this study $i = 1$).

4.5 Study areas and official data

4.5.1 Study areas and flood events

The selected area of study is the commercial zone of Bundaberg Council in Queensland, Australia. Bundaberg central city, as illustrated in Figure 4-1, is part of the Bundaberg region, north of the state's capital, Brisbane. Overall, 549 commercial buildings are situated in this suburb, including wholesale and retail trades; offices; and

transport activities (Dunford et al., 2014). As stated earlier, 75 % of these buildings have been constructed before 1980 (Dunford et al., 2014). As such, the majority of these buildings are old structures and vulnerable against flood impacts. Also, 70 % of the buildings have been constructed with masonry walls (Dunford et al., 2014), which are more vulnerable, compared to concrete and metal walls (Hawkesbury-Nepean Floodplain Management Steering Committee, 2006). From 2010, this city has experienced some extreme flood events due to the fact that it is situated in the vicinity of the Burnett River waterway. The Burnett River catchment and the Bundaberg ground elevation are illustrated in Figures 4-2 and 4-3. Empirical data used for this study has been collected after the January 2013 flood.

This flood event was a result of Tropical Cyclone Oswald and the associated rainfall. Flooding had a catastrophic effect on the Bundaberg economy, with this event being considered as the worst flood experienced in Bundaberg's recorded history. The observed peak water level along the Burnett River reached 9.53 m (Queensland Government, 2013). The propagation of the water depth is illustrated in Figure 4-4. Lifelines and infrastructure were disrupted, agricultural sectors and marine environments were impacted, and usage of coal and insurance claims dramatically increased (Queensland Government, 2013). According to comments from the communications team of the Queensland Reconstruction Authority, Bundaberg Regional Council estimated that the public infrastructure damage from the natural disaster events of 2013 was approximately AUD103 million (Hasanzadeh Nafari et al., 2016).

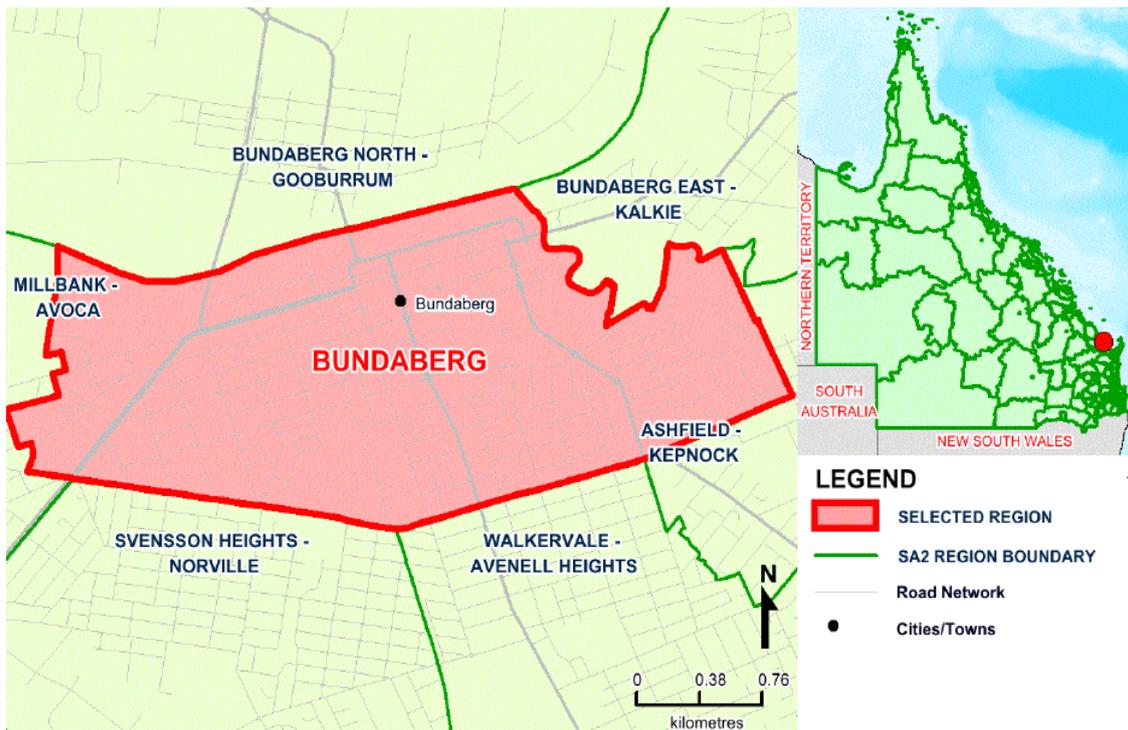


Figure 4-1: Map of Bundaberg City (Queensland Government, 2011)

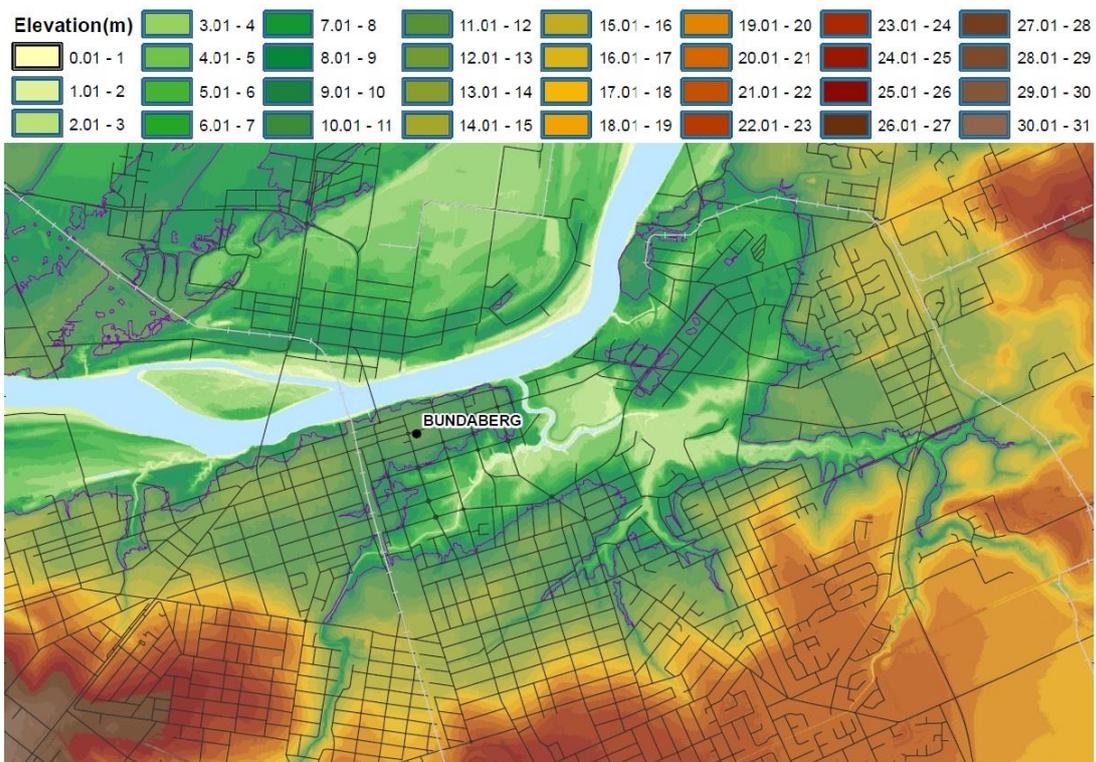


Figure 4-2: Bundaberg ground elevation (Bundaberg Regional Council, 2013a)

Chapter 4: Development and Evaluation of FLFAcs

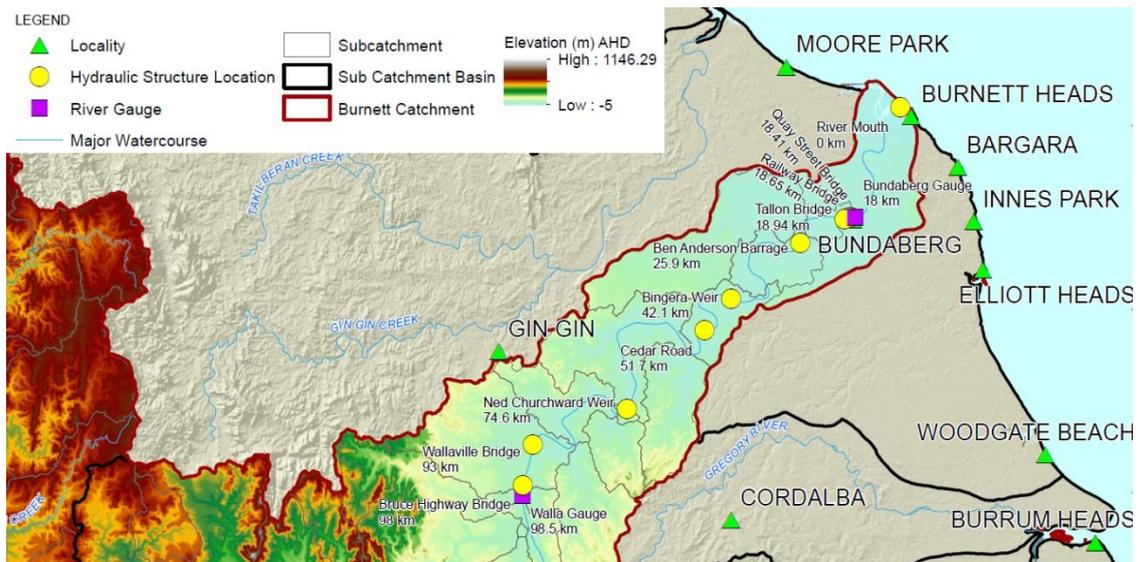


Figure 4-3: Burnett River catchment map (Bundaberg Regional Council, 2013b)

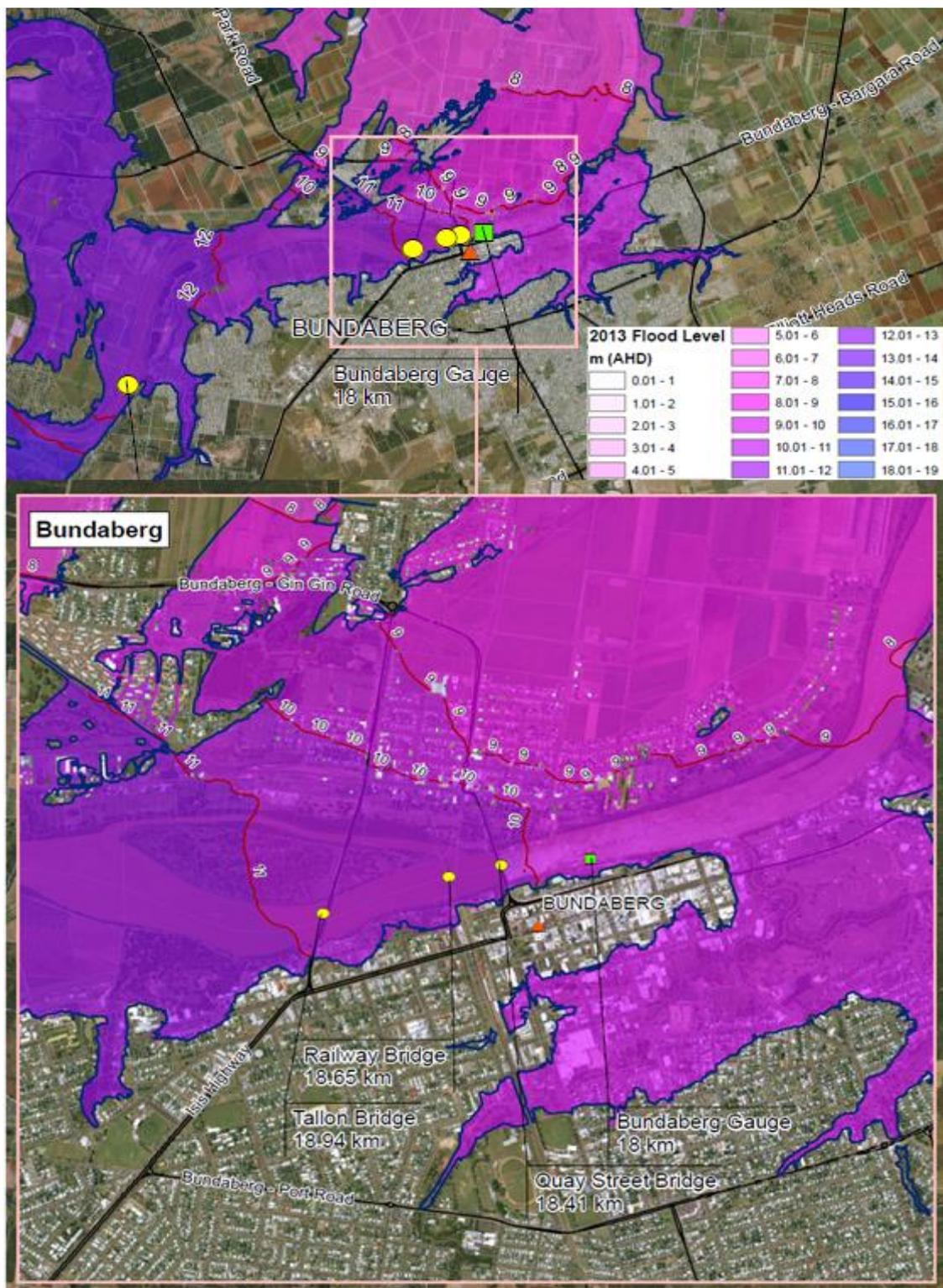


Figure 4-4: Inundation map of 2013 flood (Bundaberg Regional Council, 2013c)

4.5.2 Official flood data set

Damage surveys after floods are not a common activity for Australian governments, and most states have not dedicated any organisations to perform post-disaster data collection and surveys. Therefore, similar to many other countries, there is a high reliance on insurance company reports (Bureau of Transport Economics, 2001; Merz et al., 2010; Smith, 1994). Insurance company data sets are not generally accessible to the public, and due to confidentiality policies, companies do not release detailed records for communal use (Grahn and Nyberg, 2014). On the other hand, company methods of data gathering and collection are extremely dependent on their internal standards and policies. Therefore, the data sets may not be appropriate for deriving loss estimation models (Hasanzadeh Nafari et al., 2016; Thielen et al., 2009).

Between November 2010 and April 2011, Queensland was struck by a series of natural disasters such as extensive flooding (e.g. Maranoa and Bundaberg floods) and destructive storms. In response to the disaster events, the Queensland Government established the Queensland Reconstruction Authority. This government organisation has provided the confidential data set used for this study and employed for model calibration. As mentioned before, this data set is related to the Bundaberg central region flood in 2013 and represents the magnitude of hazard (i.e. over-floor water depth) and the extent of damages for 155 masonry wall commercial buildings.

The extent of structural damages has been collected by two post-disaster surveys and expresses the condition of flooded buildings by some descriptive terms such as: undamaged, minor, moderate, severe, and total damaged. An attached guideline explains these terms based on the affected structural components. Specifically, for each condition, the survey indicates which groups of sub-assemblies (e.g. foundation, below first floor, structure, interiors or exterior walls) start to become damaged, or become partially or entirely damaged.

Consequently, based on the average value of damaged items relative to the total value of the structure and the sub-assembly approach proposed by the HAZUS technical manual (FEMA, 2012), the description of damages have been exchanged into

percentage of damages. In this regard, the replacement value of each set of building sub-assembly compared with the total value of the building has been estimated with the help of the Australian construction cost guide (Rawlinsons, 2014) and cost estimation bills generated by local construction companies (e.g. Organized Builders’ cost estimation: <http://organizedbuilders.com.au>). Table 4-1 summarises the average contribution of sub-assembly replacement values as a percentage of the total building replacement value. Eventually, for every building, based on the estimated percentage of damage and the recorded depth of water, the percentage of damage vs. depth of water was extracted.

Table 4-1: Sub-assembly replacement values for the common types of commercial buildings (one-storey retail trade buildings and office buildings with masonry walls and slab-on-ground) as a percentage of the total building replacement value (Rawlinsons, 2014)

Assembly Components	Relative Value
Foundation and below first floor	12%
Structure framing	8%
Roof covering and roof framing	7%
Exterior walls	13%
Interiors	60%
Total	100%

4.6 Derivation and calibration of the new model

For the newly derived model in this work, the extent of damage (dh) in each level of water (h) is a function of two parameters: maximum percentage of damage D_{max} , and the rate control of function r . These two parameters, with reference to the empirical data, should be stabilised to the most appropriate values. However, because of the inherent uncertainty in the data sample and great inhomogeneity of the commercial sector (Gissing and Blong, 2004; Seifert et al., 2010), a range of estimates for the r

factor and D_{max} have been provided. With this objective, this section of the study has illustrated a bootstrapping approach to the empirical data to assist in describing confidence limits around the parameters of the depth-damage function. The following steps have been accomplished in this regard:

- The range of maximum percentage of damage (D_{max}) has been selected. This choice has been established upon the scatter of empirical data; structural characteristics (e.g. age and material); the Australian building guidelines for flood-prone areas (Hawkesbury-Nepean Floodplain Management Steering Committee, 2006); and some comparable relative flood loss models.
- Based on the defined range of D_{max} , different damage functions by different r values have been generated. Afterwards, by visual comparison among damage functions and the empirical data set, 210 different damage functions with the most appropriate values of r and D_{max} have been picked out. These curves have been created by changing the r value between 1.1 and 2, and D_{max} between 40% and 60%.
- Subsequently, resampling of empirical loss values by means of bootstrapping was carried out, and with the help of chi-square test of goodness of fit, the best-fitted value of r and D_{max} were extracted.
- Resampling of building loss values was continued up to 1000 times and for each bootstrap, the previous stage and goodness of fit test was fulfilled. By this iteration, the average of fitted values of r and D_{max} converged to the final values used for the most-likely damage curve. Furthermore, the range of D_{max} and r parameters, which were utilised for creating the minimum and maximum damage curves, were taken out from the population of fitted values.

The range of estimates we are depicting with the D_{max} and r values express the lack of confidence in the damage depth samples in representing the true uncertainty that exists in the population. Variability of these two parameters might be related to variation in characteristics of companies, change in characteristics of flood, and alteration of mitigation measures undertaken (Kreibich et al., 2010; McGrath et al., 2015). Results of

the model calibration are summarised in Table 4-2. Also, the final damage functions have been depicted in Figure 4-5.

The authors have tried to select a trend with a slight difference relative to the empirical data set. In that connection and as stated before, the most accurate values of parameters have been selected by the chi-square test of goodness of fit. As discussed further below, this matter has minimised the errors of the new model estimates relative to the observed loss records.

Table 4-2: Number of samples and range of r and Dmax values, calculated by the bootstrap and chi-square test goodness of fit

Commercial Structures with masonry walls and slab-on-ground				
Number of Samples	Parameters	Range of parameters		
		Minimum	Most-likely	Maximum
155	r	1.1	1.85	2
	D _{max}	48%	50%	60%

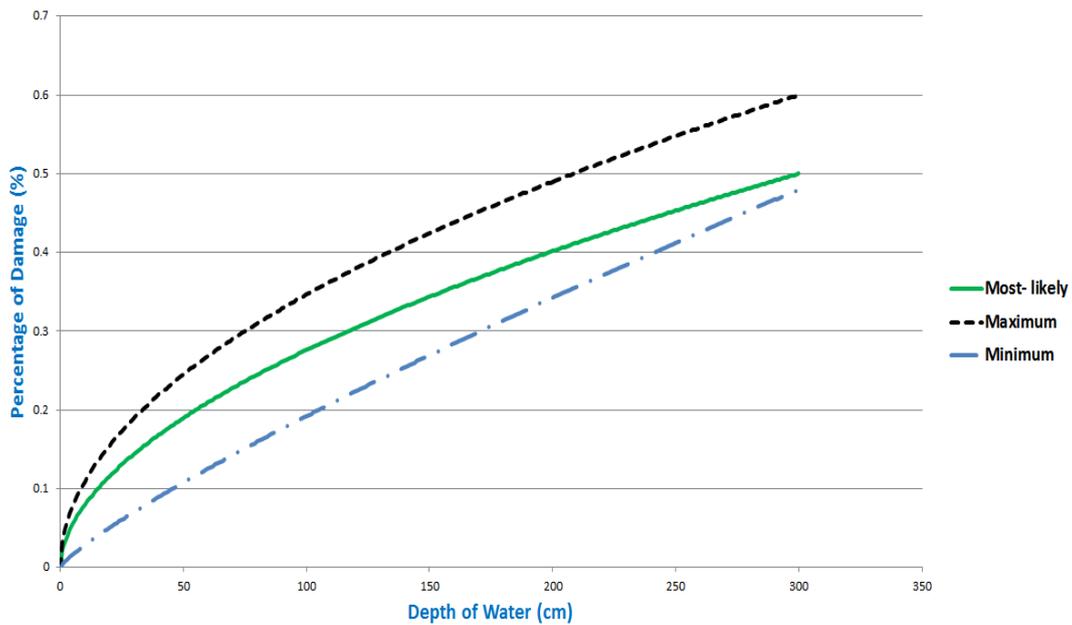


Figure 4-5: Visualisation of minimum, most-likely and maximum damage functions, calculated by bootstrap and chi-square test goodness of fit

4.7 Models comparison

4.7.1 Applied damage models

Besides FLFA_{cs}, three more damage models (one local and two from overseas) have been selected for comparison in this study.

ANUFLOOD

One of the models which have been selected for this study is the ANAFLOOD commercial stage-damage curves. As discussed previously, ANUFLOOD curves are presented as absolute losses and should be indexed to the most current dollar value. In this context, the performance of ANUFLOOD curves represented by the BMT WBM report (Huxley, 2011) have been examined and evaluated. The ANUFLOOD methodology is considered as Australia’s most commonly used commercial loss estimation model (Gissing and Blong, 2004). Therefore, awareness about the level of

uncertainty compared to the real-world damage data will amplify the cognition of decision-makers for flood risk reduction strategies in Australia.

As stated earlier, this methodology (as opposed to other applied models) expresses the magnitude of losses as a total absolute value, which includes damage to the structure and contents. Hence, for deriving the ANUFLOOD methodology, the following steps have been taken. (1) Total value of damage has been estimated by taking water depth as the hydraulic input, and size of business as the vulnerability class. It is worth noting that the majority of the buildings in the area of study are situated in the medium class of the ANUFLOOD building value. (2) In order to facilitate comparison of the ANUFLOOD methodology with other models, the values of structural damage and content damage should be separated from each other. For this matter, on the basis of building use and based on the level of water, the ratios of content losses relative to overall building losses proposed by FEMA have been utilised (FEMA, 2011). (3) For deriving structural loss ratios, the values of structural losses have been divided by the average value of assets, extracted from the national exposure information system of Australia (Dunford et al., 2014).

FLEMO_{cs} depth-damage function

Kreibich et al. (2010) proposed a new model for the estimation of flood losses in commercial sectors. This country-wide model has been prepared based on data collected for 642 flooded companies in Germany, and it is applicable for use in different spatial scales (Kreibich et al., 2010). This model has considered the hydraulic impacts of flood at five intervals (< 21 cm, 21–60 cm, 61–100 cm, 101–150 cm, and > 150 cm) of water depth. The characteristics of companies have been considered by three vulnerability classes related to the size of the company considering the number of employees (1–10, 11–100, > 100 employees); and the use of sectors (public and private sectors; production industry; corporate services and trade). Furthermore, this methodology has proposed some scaling factors to account for the effects of water contamination and level of precaution in the loss ratios (Kreibich et al., 2010). This multi-factorial relative method, which considers more damage-influencing factors, has decreased the level of

uncertainty in flood damage estimation. Hence, it would be a good example for adapting and deriving for this study area.

According to the defined vulnerability classes by FLEMO_{cs}; referring to the national exposure information system of Australia (Dunford et al., 2014); pertaining to the provided data set by the Queensland Reconstruction Authority; and applying to the Census of Population and Housing Destination Zones of Australia (Australian Bureau of Statistics, 2012), the majority and the representative group of commercial buildings are located in the medium-sized class of corporate services and trade, or the small-sized class of industry and public services. An average damage ratio for every interval of water depth has been considered based on this analysis, which gives a better comparison among the aforementioned functions.

FEMA depth-damage function

The United States Federal Emergency Management Agency (FEMA) has proposed some relative stage-damage functions in the package of Benefit-Cost Analysis (BCA: <https://www.fema.gov/benefit-cost-analysis>). These curves could be utilised for estimating both structural and content losses as a percentage of building replacement value (FEMA, 2011). It is worth noting that this method has considered depth of water as the only influencing factor of flood impacts. Also, based on building use, commercial sectors have been classified into five different categories, i.e. retail and clothing, schools, electronics, office, and light industrial. Due to the flexibility of relative functions in transferring to a new region of study (Cammerer et al., 2013; Merz et al., 2010), this model has been selected for the comparison part of this study. From the curves provided by the BCA package and on the basis of the representative group of buildings, the related curve has been utilised. Visual comparisons of the depth-damage functions provided by the three methods and relative loss ratios estimated by the ANUFLOOD model are shown in Figure 4-6.

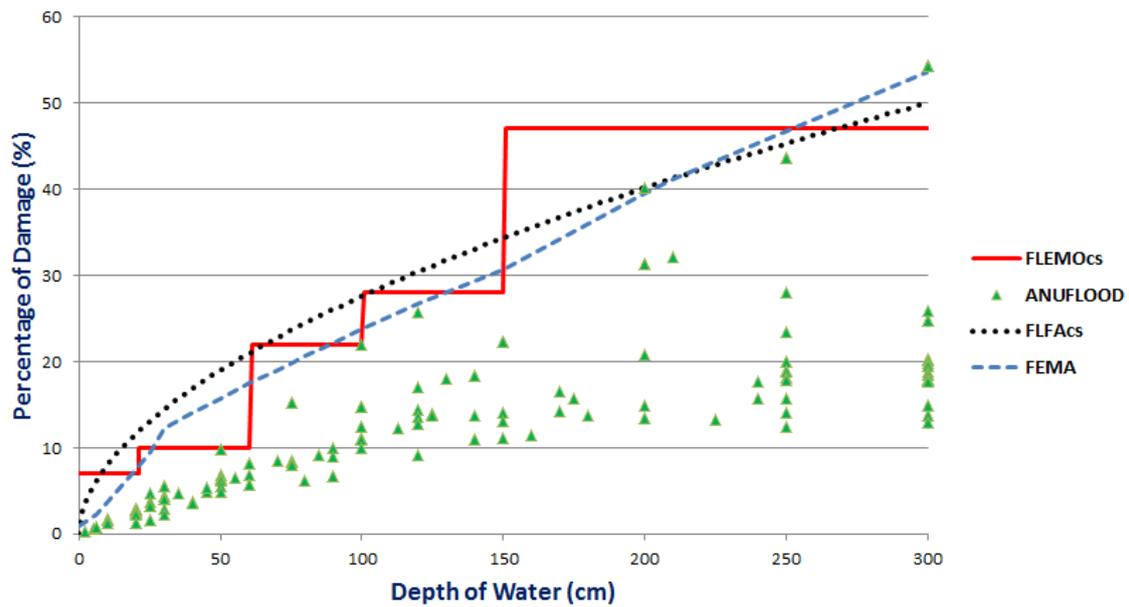


Figure 4-6: Comparison among applied damage functions from overseas; relative loss ratios estimated by the ANUFLOOD model; and the most-likely function of the newly derived method

4.7.2 Results comparison and model validation

For model validation and error estimation, a three-fold cross-validation procedure was carried out based on the data collected from the 2013 Bundaberg flood event. Due to the lack independent data for model testing, this technique of model validation has been utilised in order to limit problems like overfitting, and to give an insight on how the model will generalise to an independent dataset. The cross-validation method will create some independent data sets for training of the model (model calibration) and testing the performance of the trained model (model validation). In this regard, the shuffled data was first partitioned into three equally sized segments (folds). Subsequently, three iterations of model calibration and model validation were performed; and in each iteration, a different fold of the data was held-out for model validation while the remaining two folds were used for model calibration (Refaeilzadeh et al., 2009). In each iteration, the newly derived model was calibrated on the basis of the general idea explained in Section 5 of this study. This means that the values of rate

control r and D_{max} , for the most-likely function, are calculated by means of bootstrapping of data and the chi-square test of goodness of fit. Afterwards, the errors of the new model estimates, compared to the validation fold ratios, were evaluated by the Mean Bias Errors (MBE); the Mean Absolute Error (MAE); and the Root Mean Square Error (RMSE) tests. The MBE provides the average deviation of the estimated ratios from the validation fold ratios, and depict the direction of the error bias. A positive MBE shows an overestimation in the estimated ratios, while a negative value signifies an underestimation. The MAE represents the average absolute deviation of the estimated ratios from the validation fold ratios and is a quantity used to measure how close the estimates are to the empirical data. The RMSE also expressed the variation of the estimated ratios from the validation fold ratios and represents the standard deviation of the differences between the estimated ratios and observed ratios (Chai and Draxler, 2014; Seifert et al., 2010). The MBE, MAE and RMSE are calculated for the data set as follows:

$$MBE = \frac{1}{n} \sum_{i=1}^n e_i \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |e_i| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2} \quad (4)$$

where e_i = deviation of the estimated ratios from the validation fold ratios.

By these statistical comparisons, the performance of each newly derived function was assessed with the respective validation fold. In addition to the newly derived model and for each validation fold, errors of the other aforementioned models' estimates were calculated. Eventually, the errors were averaged for every damage model.

Additionally, resampling of observed loss ratios by means of bootstrapping was carried out to obtain a 95 % confidence interval of the mean loss ratios. This was achieved with 10,000 simulated random samples, which were drawn by replacement

from the structural loss records. If the mean loss ratio estimated by the derived models fall within the 95 % interval of the resampled data, their performance is assumed to be accepted, otherwise it can be rejected. By this approach, the performance of the applied damage models in terms of structural damage estimation in the area of study will be evaluated (Cammerer et al., 2013; Seifert et al., 2010; Thielen et al., 2008).

As summarised in Table 4-3, the K-fold cross-validation procedure shows that the estimates of FLFA_{cs} are good. The MBE values show no bias; the MAE varies between 4 and 5 % (5 % on average); and the RMSE changes between 5 and 8 % (6 % on average). The results of other models show larger average deviations from the validation fold ratios. Also, the other models have larger average values of absolute deviation and greater values of standard deviation. This matter signifies a higher variation in the errors of the FLEMO_{cs}, FEMA and ANUFLOOD model estimates. As summarised in Figure 4-7, the individual differences between the estimated ratios and validation folds ratios (residuals) in FLFA_{cs}, in contrast to other models, have less magnitude and variation. The FLFA_{cs} clearly achieves better results than the models that are not calibrated with the local damage data.

In addition, the performance of all flood loss models used to estimate the mean loss ratios is summarised in Table 4-4. It can be observed that the result of the new model with the most-likely functional parameters, lie within the confidence intervals and its performance is acceptable. However, results of other models do not lie within the confidence intervals of the mean loss ratios and their performance is rejected in this area of study. This issue and the K-fold cross-validation procedure illustrates the importance of model calibration with the empirical local data sets, particularly when the water depth is the only hydraulic factor considered (Cammerer et al., 2013; Chang et al., 2008; McBean et al., 1986). Although the results of the FLEMO_{cs} and FEMA models do not lie within the confidence intervals, errors of their estimates are not too significant, and their performances are much better than the ANUFLOOD model.

In this study and for investigating cause-and-effect relations between flooding and damage, water depth is taken into account as the most dominant influencing factor of

Chapter 4: Development and Evaluation of FLFAcs

flood hazard; and the materials of buildings, absence of basement, use of buildings, number of storeys, age of building, and height of storeys have been considered as the vulnerability factors of buildings (Kelman and Spence, 2004; Menoni et al., 2012). Although damage magnitude could be reliant upon more factors (Grahm and Nyberg, 2014), by calibrating the loss function with the empirical data set collected from the real-world and providing an empirically-based curve, the damage model has been validated for use in the conditions of the study area (McBean et al., 1986).

Table 4-3: Numerical comparison and error estimation for performance of the applied damage functions (MBE: Mean Bias Error; MAE: Mean Absolute Error; RMSE: Root Mean Squared Error)

	MBE				MAE				RMSE			
	FLFAcs	FLEMOcs	FEMA	ANUFLOOD	FLFAcs	FLEMOcs	FEMA	ANUFLOOD	FLFAcs	FLEMOcs	FEMA	ANUFLOOD
Fold 1	0.00	-0.02	-0.01	-0.15	0.05	0.06	0.06	0.15	0.06	0.08	0.08	0.18
Fold 2	0.00	-0.02	-0.01	-0.17	0.04	0.05	0.05	0.17	0.05	0.06	0.07	0.19
Fold 3	0.00	-0.02	-0.01	-0.16	0.05	0.06	0.06	0.17	0.08	0.10	0.09	0.20
Average	0.00	-0.02	-0.01	-0.16	0.05	0.06	0.06	0.16	0.06	0.08	0.08	0.19

Table 4-4: Comparison of mean loss ratios estimated by the applied damage models with the resampled loss data (95% confidence interval)

	FLFA_{cs}		FLEMO_{cs}		FEMA		ANUFLOOD	
	Mean loss ratios	Within 95% interval	Mean loss ratios	Within 95% interval	Mean loss ratios	Within 95% interval	Mean loss ratios	Within 95% interval
Fold 1	0.313	Yes	0.292	No	0.296	No	0.157	No
	0.306 (2.5 th percentile)				0.313 (97.5 th percentile)			
Fold 2	0.291	Yes	0.270	No	0.280	No	0.114	No
	0.284 (2.5 th percentile)				0.292 (97.5 th percentile)			
Fold 3	0.307	Yes	0.281	No	0.296	No	0.149	No
	0.302 (2.5 th percentile)				0.308 (97.5 th percentile)			
All records	0.304	Yes	0.280	No	0.291	No	0.140	No
	0.297 (2.5 th percentile)				0.304 (97.5 th percentile)			

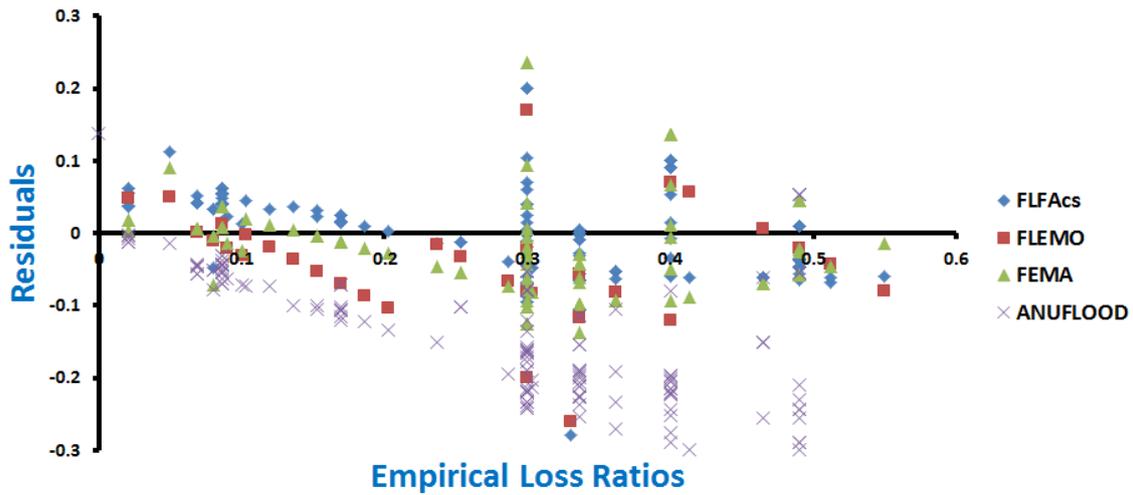


Figure 4-7: Residual plot used for comparing performance of the selected damage functions relative to the empirical loss ratios

4.8 Conclusions

Statistical analyses emphasise the significance of commercial building flood losses for the economics of Australia. However, Australian models for commercial loss estimation are still limited and their results are subjected to a high level of uncertainty.

The proposed approach presented in this chapter has attempted to quantify the magnitude of direct damages of commercial structures. This approach has suggested a damage function for quickly describing the extent of flood losses. The new function (FLFA_{cs}) can be utilised for different purposes such as flood management tasks or insurance issues. In this model, water depth is taken into account as the most dominant influencing factor of flood hazard; and materials of buildings, use of buildings, number of storeys, age of building, and height of storeys have been considered as the vulnerability factors. In this regard, the newly derived model has been calibrated for the geographical conditions of Australia by means of empirical data collected from the 2013 flood in Bundaberg, Australia. Also, inherent uncertainty of the new model as a result of insufficient data and the great variation of commercial building structures have been

considered. Although non-residential building losses are less about structural damage and more about damage to contents, due to limited availability of data, this model has been built only for structural damages. However, as a result of simplicity and flexibility of the new function, it is possible for it to be developed by future researches, even for using in another region of study.

In addition, the performance of the new model in comparison to the empirical data has been contrasted with two damage functions from overseas and one damage model from Australia. Furthermore, statistical comparison and numerical analysis with regards to estimating the level of uncertainty and validating the applied damage models were conducted. These analyses show that accuracy of results is totally dependent on model calibration. Also, they show that the results of the Australian model are no longer sufficiently accurate. Hence, there is an urgent need for a project to develop new functions for commercial flood damage estimation.

Since the vulnerability of commercial buildings to flood is of particular interest to the insurance industry, databases of insurance claims can benefit this research considerably. Therefore, reconciliation with insurance claims data and consideration of more flood loss events will benefit future works. On the other hand, further research will be aimed at incorporating more influencing factors of hazard, exposure and vulnerability; considering content damages as well as structural damages; taking into account more variations of commercial sectors; and last but not least, enhancing the level of precision in damage documentation procedures.

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Chapter 4: Development and Evaluation of FLFAcs

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5 FLOOD LOSS

MODELLING WITH FLF-IT

A NEW FLOOD LOSS FUNCTION FOR ITALIAN RESIDENTIAL STRUCTURES [Published Chapter]³

5.1 Abstract

The damage triggered by different flood events costs the Italian economy millions of euros each year. This cost is likely to increase in the future due to climate variability and economic development. In order to avoid or reduce such significant financial losses, risk management requires tools which can provide a reliable estimate of potential flood impacts across the country. Flood loss functions are an internationally accepted method for estimating physical flood damage in urban areas. In this study, we derived a new flood loss function for Italian residential structures (FLF-IT), on the basis of empirical damage data collected from a recent flood event in the region of Emilia-Romagna. The function was developed based on a new Australian approach (FLFA), which represents the confidence limits that exist around the parameterised functional depth-damage relationship. After model calibration, the performance of the model was validated for

³ Hasanzadeh Nafari, R., Amadio, M., Ngo, T., Mysiak, J., 2017. Flood loss modelling with FLF-IT: A new flood loss function for Italian residential structures. *Nat. Hazards Earth Syst. Sci.* 17, 1047–1059

the prediction of loss ratios and absolute damage values. It was also contrasted with an uncalibrated relative model with frequent usage in Europe. In this regard, a three-fold cross-validation procedure was carried out over the empirical sample to measure the range of uncertainty from the actual damage data. The predictive capability has also been studied for some sub-classes of water depth. The validation procedure shows that the newly derived function performs well (no bias and only 10% mean absolute error), especially when the water depth is high. Results of these validation tests illustrate the importance of model calibration. The advantages of the FLF-IT model over other Italian models include calibration with empirical data, consideration of the epistemic uncertainty of data, and the ability to change parameters based on building practices across Italy.

5.2 Introduction

Floods are the natural hazards that cause the largest economic impact in Europe today (European Environment Agency, 2010). Italy is no exception, with about 80% of its municipalities being exposed to some degree of hydrogeological hazards (Zampetti et al., 2012). Regarding flood hazard frequency, 8% of Italy's territory and 10% of its population are exposed to a flood probability of once every 100 to 200 years (ANCE/CRESME, 2012; Trigila et al., 2015). This issue is reflected in over a billion euros spent from 2009 to 2012 on recovery from extreme hydrological events (Zampetti et al., 2012). Italy is, in fact, the European country where floods generate the largest economic damage per annum (Alfieri et al., 2016). This is especially worrisome considering that the frequency of extreme flood losses may be doubled at least by 2050 in Europe due to climatic change factors and urban expansion (Jongman et al., 2014). Climate variability already affects rainfall extremes and the peak volumes of discharge in rivers (Alfieri et al., 2015; Karagiorgos et al., 2016). Relentless urban sprawl within catchments alters the water run-off speed and propagation while increasing the value of exposed land use (Barredo, 2009). In order to effectively prevent massive losses, disaster risk management requires estimation well in advance of the frequency and magnitude of potential flood events, and their consequences in terms of economic

damages (Elmer et al., 2010; Hammond et al., 2015; Kaplan and Garrick, 1981; Neale and Weir, 2015; Thielen et al., 2008; UNISDR, 2004). Therefore, it is indispensable to provide decision makers with reliable assessment tools that are able to produce such knowledge, after which an efficient risk reduction strategy can be adequately planned (Emanuelsson et al., 2014; McGrath et al., 2015; Merz et al., 2010; Penning-Rowsell et al., 2005).

In general, flood losses are classified as marketable (tangible) or non-marketable (intangible) values, and as direct or indirect (Jonkman, 2007; Kreibich et al., 2010; Meyer et al., 2013; Molinari et al., 2014a; Thielen et al., 2005). Direct damage takes place when the floodwater physically inundates buildings and structures, whereas indirect damage accounts for the consequences of direct damage on a wider scale of space and time (Hasanzadeh Nafari et al., 2016c). The tools employed to assess flood risk consist of a variety of damage models, with differing methods depending on the type of accounted losses. While input-output models, computable general equilibrium models and other econometric tools are often used to estimate indirect economic losses (Carrera et al., 2015; Hallegatte, 2008; Koks et al., 2015), the focus of most flood damage models is still on the estimation of direct, tangible losses using stage-damage curves. Stage-damage curves or flood loss functions are used to depict a relationship between water depth and economic damage for a specific kind of structure or land use (Jonkman et al., 2012; Kreibich and Thielen, 2008; Merz et al., 2010; Messner et al., 2007; Thielen et al., 2009). Damage curves can be empirical or synthetic. Empirical curves are drawn based on actual data collected from one specific event. Due to the differences in flood and building characteristics, they cannot be directly employed in different times and places (Gissing and Blong, 2004; McBean et al., 1986). To resolve this issue, general synthetic curves based on a valuation survey have been created for different types of buildings. Valuation surveys assess how the structural components are distributed in the height of a building (Barton et al., 2003; Smith, 1994). Afterwards, the magnitude of potential flood losses is estimated based on the vulnerability of structural components and via “what-if” questions (Gissing and Blong, 2004; Merz et al., 2010). Damage functions can also be distinguished as absolute or relative. The first type states

the damage directly in monetary terms, while the relative type states the damage as a percentage of the total exposed value, which can refer to the total replacement value or the total depreciated value (Kreibich et al., 2010). Relative functions have an advantage over absolute functions, namely that they are more flexible for transfer to different regions or years since the damage ratio is independent of the changes in market values (Merz et al., 2010). Still, both types are developed on sample areas which have particular geographical characteristics that affect both the quality of the exposed value and the flood phenomena (McGrath et al., 2015; Proverbs and Soetanto, 2004). Therefore, transferred models may carry a high level of uncertainty, unless they are calibrated with an empirical dataset collected from the new study area (Cammerer et al., 2013; Hasanzadeh Nafari et al., 2015; Molinari et al., 2014b).

Although Italy has seen several flood disasters in recent years, flood records do not enable development or validation of a national-loss flood function because the information is still poor, fragmented and inconsistent. This issue largely depends on the lack of an established official procedure for the collection and the storage of damage data (Molinari et al., 2014b). Another obstacle is the heterogeneity across different regions of digital geographic information, which is the key to correctly representing the driving factors of exposure and vulnerability influencing the sustained damage. Few attempts at drawing a depth-damage relation from post-disaster reports have been made (Amadio et al., 2016; Luino et al., 2009; Molinari et al., 2014b, 2012; Papathoma-Köhle et al., 2012; Scorzini and Frank, 2015), while other uncalibrated synthetic functions have been derived from pan-European studies (Huizinga, 2007). The use of such uncalibrated functions on the Italian territory has proven troublesome (Amadio et al., 2016), showing a large degree of uncertainty.

Our research aims to calibrate and validate a new relative flood loss function for Italian residential structures (FLF-IT) based on real damage data collected from one large river flood event in the region of Emilia-Romagna at the beginning of 2014. The focus of this study is on direct tangible damage, and the spatial scale is of the order of

individual buildings. This research builds on a newly derived Australian approach called FLFA (Hasanzadeh Nafari et al. 2016a, 2016b).

5.3 Case study

The region of Emilia-Romagna is located in northern Italy, on the southern side of the Po River, the longest of all Italian rivers. This region has the greatest flood-prone area both in relative and absolute terms: about 10,000 km², including 64% of the population is exposed to a medium flood probability (return period between 100 and 200 years), while 2,500 km² including 10% of the population, is exposed to a high probability (return period between 20 and 50 years) (Trigila et al., 2015). This includes more than half of the region's territory. Our empirical data come from a flood generated by the Secchia River in 2014 near the town of Modena, in the central part of Emilia-Romagna.

5.3.1 Event description

January 2014 was a dramatic month for floods in Italy, with 110 flood events recorded over a span of 23 days due to extreme meteorological conditions. Severe precipitations hit central Emilia-Romagna between the 17th and the 19th of January, with an areal mean of 125 mm of cumulative rain over 72 hours flowing in the Secchia catchment. The increase in the river flow volumes caused heavy stress on the levees, which stand 7-8 meters over the flood plain. At around 06:00 LT, approximately 10 m of the eastern Secchia levee was overwashed and breached at the top by 1 m, which initiated flooding of the countryside. In 9 hours, the levee section was completely destroyed for a length of 80 meters, spilling 200 m³ s⁻¹ in the surrounding plain and flooding nearly 65 km² of rural land (Figure 5-1) (D'Alpaos et al., 2014). Seven municipalities were affected, with the small towns of Bastiglia and Bomporto suffering the largest share of losses. Both towns, including their industrial districts, remained flooded for more than 48 hours. The total volume of water inundating the area was estimated to be around 36 million m³ (D'Alpaos et al., 2014).

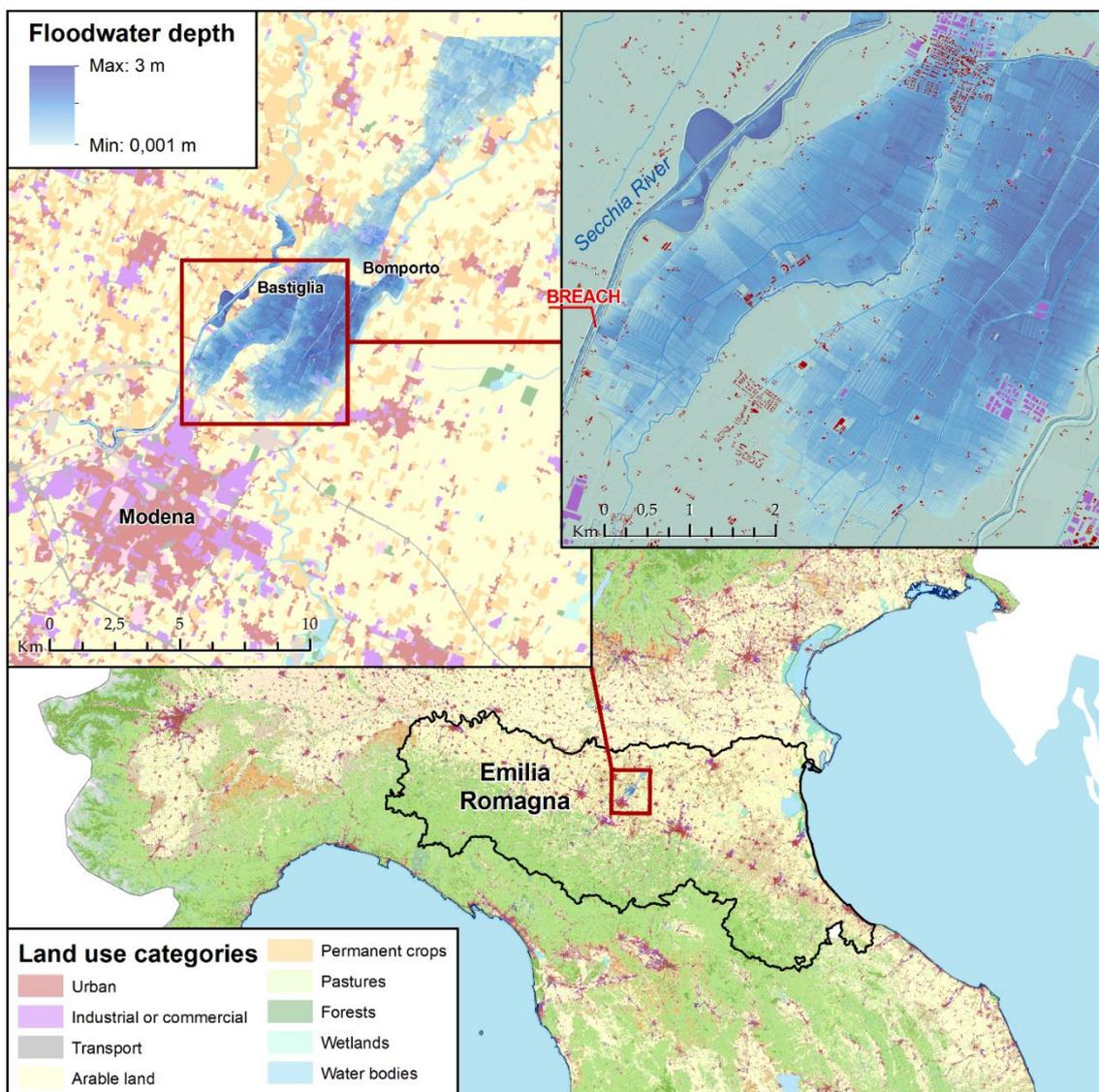


Figure 5-1: Identification of case study, flooding from the river Secchia during January 2014 in central Emilia-Romagna, northern Italy

5.3.2 Data description

The information about cumulative water depths comes from the hydraulic simulation of the event produced by the technical-scientific committee in the official report (D’Alpaos et al., 2014; Vacondio et al., 2014). The extent of the simulated flood is nearly 5 km², with an average depth of 1 m. The flow volume at the breach is calculated using the 1-D model HEC-RAS calibrated on recorded observations from the event. The

evolution of the flooding is simulated by a 2-D hydraulic model using the finite-volume method over a digital terrain model (DTM) obtained by lidar scans at a 1 m resolution. The simulation also accounts for the gradual change in the size of the breach from 10 to 80 meters (Vacondio et al., 2014).

A database of damage declared by residential properties has been made available for this research by the local authorities. Damage records are listed by address for the three municipalities of Bastiglia (70% of the total damage), Bomporto (24%), and Modena (6%). The total damage sums up to EUR 41.5 million, of which 54% is damage to structural parts, including installations; 33% is damage to movable contents, meaning furniture and common domestic appliances; and 13% is represented by registered vehicles, such as cars and motorcycles. For the purpose of our study, only the structural damage is considered. The recorded damage is compared to the average market values of the residential properties, as reported by the cadastral map for the 6 months preceding the flood event (Agenzia delle Entrate, 2014). The majority of residential structures in the area share the same general characteristics: they are brick or concrete buildings built in the last 30 years, with no underground basement or parking (slab on ground). Houses have at least two or three floors. However, only the ground floors have been affected in this particular event.

The information related to water depth, total structural damage and average market value is linked together at the building scale (Fig. 5-2) by combining the street number points and residential buildings perimeters from the official regional geodatabase (Regione Emilia Romagna, 2011). The mean of cumulative water depths simulated by the hydraulic model is calculated within the area of each building unit. Accordingly, each address linked to a damage record is first georeferenced as a street number point; then the points falling within the same building unit are summed into an aggregated value representing the total structural damage that occurred in that building, including private dwellings and common parts. This spatial join is necessary since building perimeters do not include any information about addresses. The procedure is performed successfully for EUR 21.7 million, corresponding to 97% of the total residential

damage. The remaining 3% of records are excluded due to incomplete addresses or inconsistency with the spatial data. Percentages of damage vs. depths of water for all 613 final samples are depicted in Fig. 5-3.

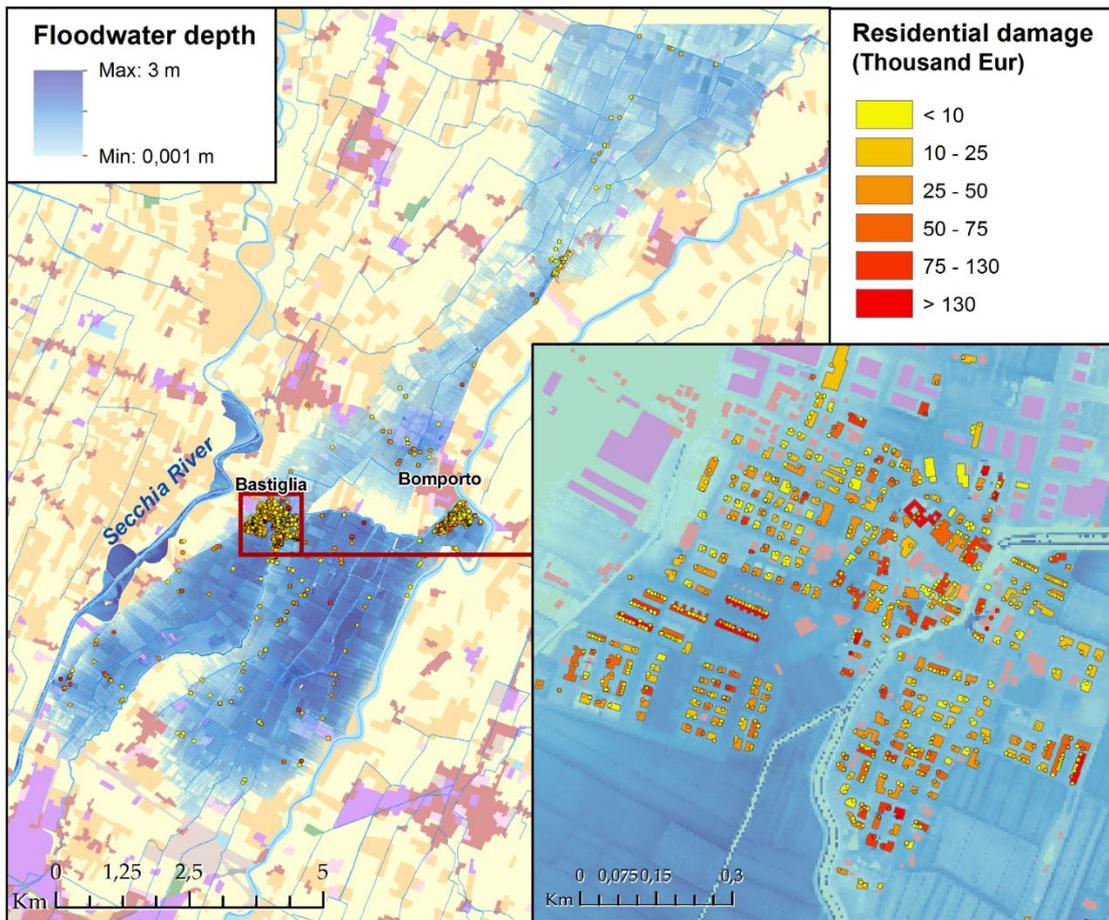


Figure 5-2: Visualisation of the empirical damage records suffered by the individual dwellings during the flood event of 2014. Records are projected to official street number points by using their "address" field. The information is then transferred from the points to the building features that contains them. The point records that fall within the same building perimeter are summed up into one aggregated damage value for each residential building. About 97% of damage records are correctly projected. The remaining 3% of damage records are discarded due to inconsistent projection, incomplete address or gaps in the record data. The colour gradient (yellow to red) indicates the magnitude of the damage for both individual points and building units.

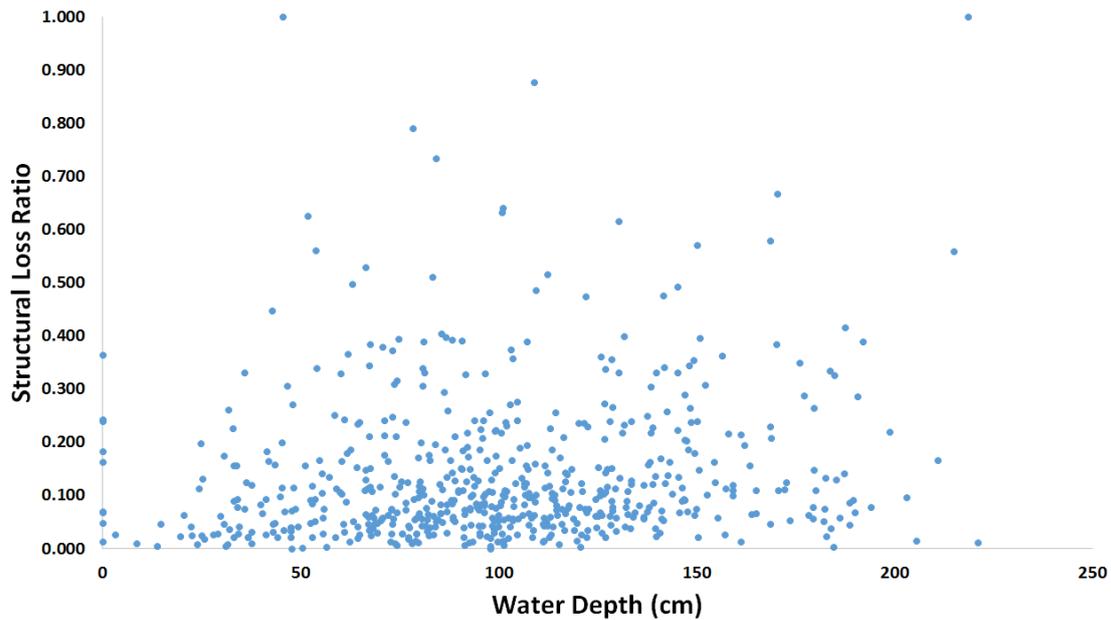


Figure 5-3: Empirical data utilised to calibrate the FLF-IT model (613 relative damage records in the original dataset)

5.4 The FLFA method

The FLFA method is based on a simplified synthetic approach called the sub-assembly method, proposed by the Hazus technical manual (FEMA, 2012). This method measures the extent of losses for each stage of floodwater and suggests a flexible curve that accounts for the variability in the characteristics of structures. In the first step, one or more representative building categories are selected from the study area. The ratio of damage for every stage of water and within each category of the building is a function of the vertical distribution of structural components (i.e. vulnerability and the total value exposed to flood) (Lehman and Hasanzadeh Nafari, 2016). More specifically, each structural component starts suffering damage after a specific stage is reached. Commonly the first decimetres of water cause damage to some of the most valuable items, such as walls, floors, insulation and electrical wiring (FEMA, 2012). Accordingly, the relationship between the damage percentage (d_h) and water depth can be described by a root function (Cammerer et al., 2013; Elmer et al., 2010; Kreibich and

Thieken, 2008). The following function (1) was developed by Hasanzadeh Nafari et al. (2016a) for the Australian case study:

$$d_h = \left(\frac{h}{H}\right)^{\frac{1}{r}} \times D_{max} \quad (1)$$

The root (r) controls the rate of alteration in the percentage of damage relative to the growth of the water depth (h) over a total height (H) of the floor. The D_{max} is the total percentage of damage corresponding to the total height of the floor. A higher value of r means a faster increase in the rate of damage. The obtained curve is then adjusted and calibrated using the empirical data collected from the selected study area. Hence, this approach is defined as an empirical-synthetic method. Due to the inherent uncertainty in the data sample, the study employed a bootstrapping approach, which produces three stage-damage functions (i.e. most likely, maximum and minimum damage functions) for each type of building. This range of estimate describes confidence limits around the functional parameters and represents the uncertainty that exists in the data sample. The advantages of this simplified synthetic approach include calibration with empirical data, a better level of transferability in time and space, consideration of the epistemic uncertainty of data, and the ability to change parameters based on building practices across the world.

5.5 Calibration of FLF-IT

Based on the formula represented previously, the model calibration process includes choosing the most appropriate values for the root function and the maximum percentage of damage (i.e. r and D_{max} , respectively), with reference to the empirical dataset (Hasanzadeh Nafari et al., 2016a). The selection will be made by the chi-square test of goodness of fit, to minimise predictive errors. Also, instead of a deterministic regression analysis, this study has relied on the probabilistic relationship among the percentage of damage and other damage-related parameters (i.e. building and flood characteristics) (Hasanzadeh Nafari et al., 2016b). In this regard, a bootstrapping approach has been employed to resample the damage data 1,000 times. This method assists in exploring the

confidence limits around the parameters and illustrates the epistemic uncertainty of the empirical damage data (Lehman and Hasanzadeh Nafari, 2016). To be more specific,

- first, the original dataset including 613 data points was resampled using a bootstrapping approach;
- for the new resample, the most appropriate value of the root function and the maximum percentage of damage were selected by the chi-square test of goodness of fit;
- the two previous steps were repeated 1,000 times, and 1,000 sets of parameters (i.e. r and D_{max}) were generated as the result;
- finally, by the above iteration, the averages of the 1,000 calibrated parameters converged to a fixed value considered as the most likely scenario. The most likely parameters produce the smallest cumulative error compared to the actual damage data.
- Also, from the 1,000 sets of parameters generated above, the function that maximises the depth-damage relationship was taken as a maximum damage curve, and the observation that created the minimum depth-damage relationship was considered for the minimum depth-damage function.

Results of the model calibration are presented in Table 5-1 and Fig. 5-4.

Table 5-1: Number of samples and range of r and D_{max} values, calculated by the bootstrap and chi-square test of goodness of fit

Number of Samples	Parameters	Range of parameters		
		Minimum	Most likely	Maximum
613	r	2.7	2	1.7
	D_{max}	10%	20%	40%

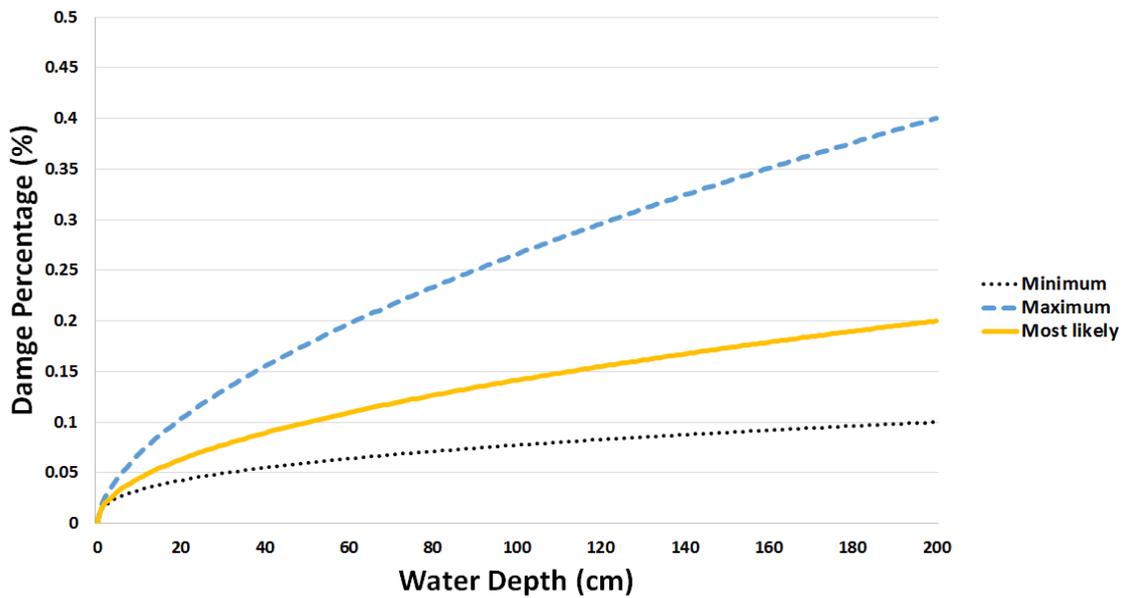


Figure 5-4: Visualisation of minimum, most likely and maximum damage functions, calculated by bootstrap and chi-square test of goodness of fit

5.6 Model validation

5.6.1 Applied damage models

Besides FLF-IT, the Damage Scanner as an uncalibrated relative model with frequent usage in Europe has been selected for comparison in this study. The Damage Scanner model (de Bruijn, 2006; Klijn et al., 2007) is based on depth-damage curves previously developed by the synthetic approach in the Netherlands using data from what-if analyses at the building scale (Kok et al., 2004). These curves estimate the magnitude of damage separately for building structure and movable content. The damage is expressed in relation to an average maximum damage value per square meter, which varies according to land use classes (e.g. residential, industrial, agriculture, and infrastructure). The Damage Scanner model has been employed for predictive purpose in various studies (Aerts and Botzen, 2011; Bouwer et al., 2010; de Moel et al., 2011; Koks et al., 2012; Poussin et al., 2012; Ward et al., 2011), and it has been more recently updated including additional land use sub-classes (de Moel et al., 2013; Koks et al., 2014). The

uncertainty of Damage Scanner has been investigated in comparison to other damage models (Bubeck et al., 2011; Jongman et al., 2012), and its transferability has been evaluated for use in different areas of study such as northern Italy (Amadio et al., 2016). Damage Scanner is, in fact, easy to tailor to land use description available for Italy, and because it expresses damage in relative terms, it can be adapted to work on region-specific maximum values. For the purpose of comparison with FLF-IT, the curve related to residential structure damage has been selected from the Damage Scanner set and applied at building scale to the residential units using the same average market values and simulated water stages employed to produce the FLF-IT. It is worth noting that the predicted absolute damage values are calculated by multiplying the estimated loss ratio by the average market value and the area of each property.

5.6.2 Result comparison and model validation

Results of the applied damage models have been compared with the observed loss data, and their performances have been validated in contrast to real damage data. Due to the lack of an independent dataset, a three-fold cross-validation technique was employed for this purpose (Seifert et al., 2010). Accordingly, the original damage records including 613 data points were first shuffled and partitioned into three equally sized subsets. Then, three iterations of model calibration and model testing were performed. In each iteration, one subset including 204 samples was singled out for model testing, while the remaining two parts including 409 data points were used for model calibration (Refaeilzadeh et al., 2009). Model calibration in each iteration was performed based on the approach explained earlier. Eventually, the loss ratio of the held-out subset was estimated by the FLF-IT model calibrated without it, and the results were compared with the actual records. Errors including the mean bias error (MBE), the mean absolute error (MAE), and the root mean square error (RMSE) were calculated and averaged over all three iterations. The MBE illustrates the direction of the error bias (i.e. a positive MBE shows an overestimation in the predicted values, while a negative MBE depicts an underestimation); the MAE shows how close the estimates are to the actual damage ratios; and the RMSE signifies the variation of the predicted ratios from

the actual records (Chai and Draxler, 2014; Seifert et al., 2010). In addition to FLF-IT and for each iteration, errors of the Damage Scanner model’s estimates were calculated. The results are presented in Table 5-2.

Table 5-2: Error estimation for the performance of the FLF-IT model (MBE: mean bias error; MAE: mean absolute error; RMSE: root mean squared error)

	MBE		MAE		RMSE	
	FLF-IT	Damage Scanner	FLF-IT	Damage Scanner	FLF-IT	Damage Scanner
Iteration 1	0.015	0.152	0.092	0.188	0.119	0.212
Iteration 2	-0.010	0.125	0.104	0.177	0.157	0.204
Iteration 3	-0.009	0.125	0.091	0.164	0.133	0.188
Average	0.00	0.13	0.10	0.18	0.14	0.20

This table clearly shows that FLF-IT has a better performance than the Damage Scanner model, which is not calibrated with the local damage data. The average of the MBE over all iterations shows no bias and represents only around 1% bias in each iteration. The MAE is 10% on average, and RMSE ranges between 12 and 16% (14% on average). The results of the Damage Scanner model show 13% average deviation from the validation subsets ratios, larger average values of absolute error, and higher variation of the predicted ratios from the actual records. Overall, the small value of the deviations and the low variation of the errors signify that the new model performance is accurate.

The predictive capability has also been studied for some sub-classes of water depth. By this test, the performance of the applied damage models will be evaluated for different stages of the flood. Figs. 5-5 and 5-6 show the precision of the results and the number of relative damage records for seven different sub-classes of water depth. These figures clearly show that the uncertainty of FLF-IT is less than the Damage Scanner model, and the results justify the overall better performance of the FLF-IT model. This

test shows that the application of the Damage Scanner model using the original uncalibrated maximum damage values leads to overestimating the actual damage that occurred during this flood event, especially when the water depth is high. In contrast to Damage Scanner, FLF-IT performs well specifically when the flood is deep, the extent of damage is more considerable, and the prediction performance of the model is more important. The high number of samples with a depth more than 60 centimetres supports the reliability of this outcome.

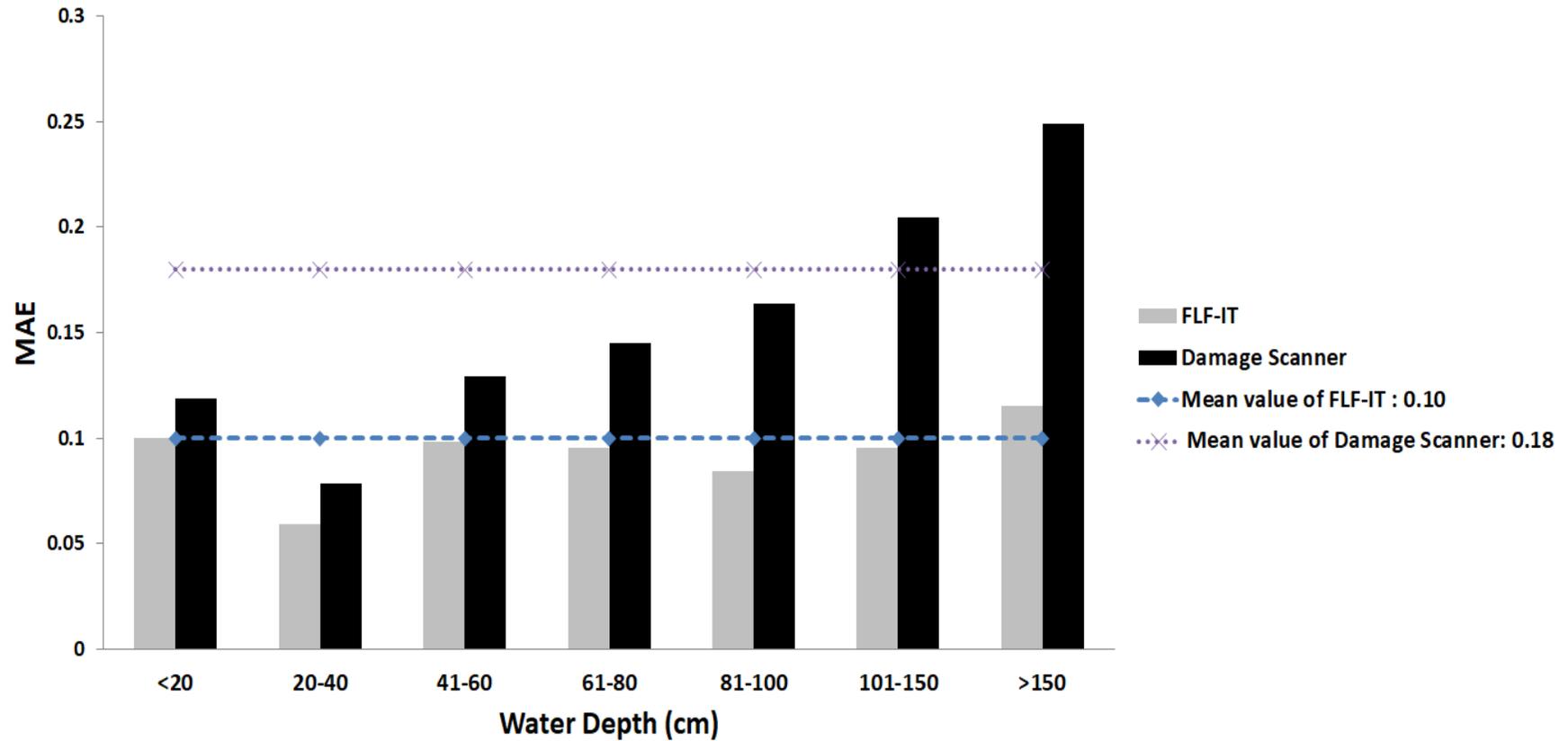


Figure 5-5: Comparison of the flood damage estimation models' precision per water-depth class (MAE: mean absolute error; number of damage records for each sub-class of water depth, respectively, is 14, 36, 52, 96, 125, 222, and 68)

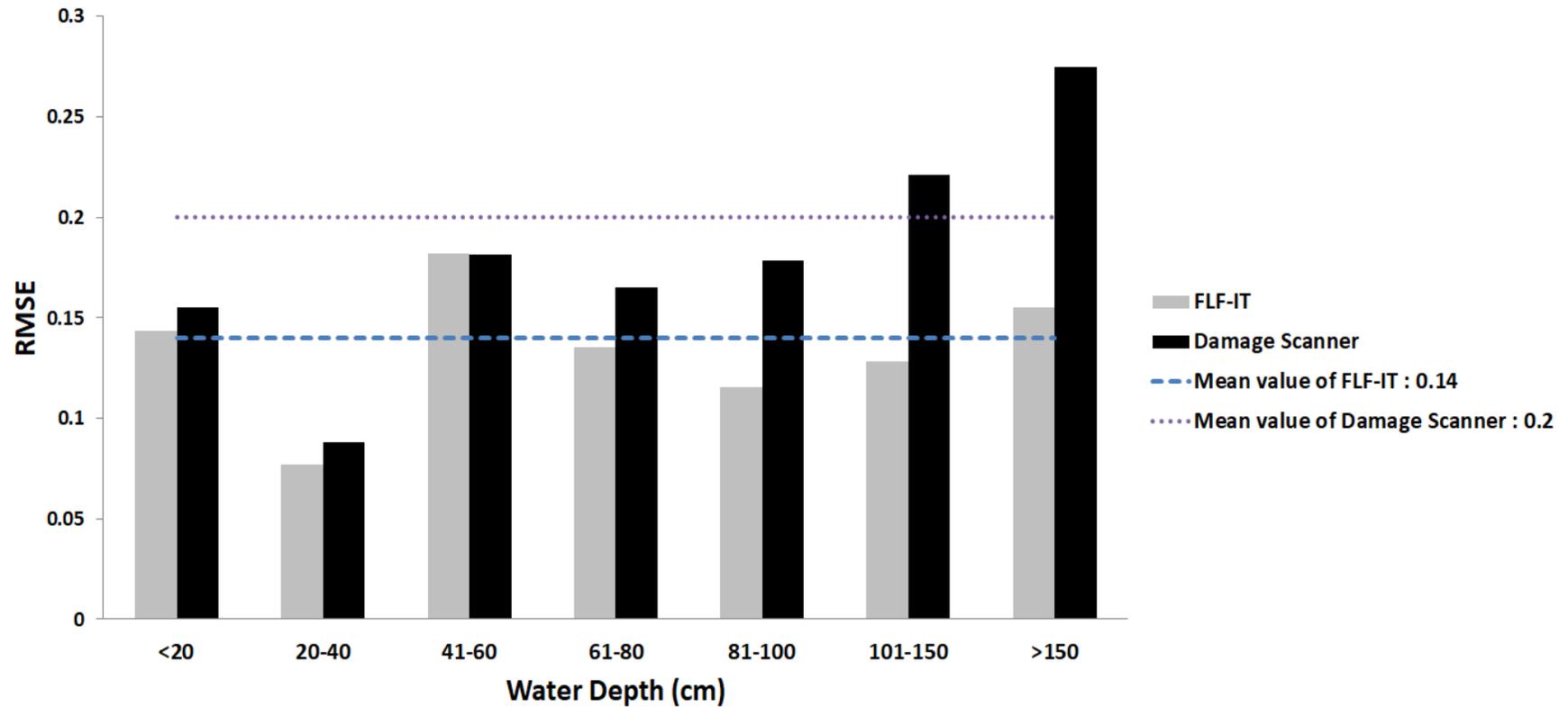


Figure 5-6: Comparison of the flood damage estimation models' precision per water-depth class (RMSE: root mean square error; number of samples for each sub-class of water depth, respectively, is 14, 36, 52, 96, 125, 222, and 68)

In addition to the above comparison on the loss ratios, the performance of the model is also validated for predicting the absolute damage values. As stated before, the overall reported loss for the 613 cases (building fabric) amounted to EUR 21.7 million. In this regard and for each iteration, the absolute damage records are resampled using the bootstrapping approach 10,000 times, and the 95% confidence interval of the total losses was calculated. If the total damage value estimated by the models falls within the 95% confidence interval, their performance is accepted. Otherwise, it is rejected (Cammerer et al., 2013; Seifert et al., 2010; Thielen et al., 2008). By this approach, the performance of the applied damage models in terms of structural damage estimation in the area of study will be evaluated. The results are presented in Table 5-3, which shows that the results of all iterations of the FLF-IT model with the most likely functional parameters r and D_{max} lie within the 95% confidence intervals, and the FLF-IT model has an acceptable performance. However, results of Damage Scanner do not lie within the confidence intervals of the mean loss ratios, and its performance is rejected in this area of study. Fig. 5-7 represents the workflow and the methodological steps of this study.

Table 5-3: Comparison of total absolute losses estimated by FLF-IT with the 95% confidence interval of the resampled damage records

	95% confidence interval	Estimated damage values (in 10 ⁶ EUR)			
		FLF-IT	Within 95% interval	Damage Scanner	Within 95% interval
Iteration 1	4.88-6.8 (2.5 th -97.5 th percentile)	6.5	Yes	16.2	No
Iteration 2	5.81-7.8 (2.5 th -97.5 th percentile)	7.7	Yes	15.6	No
Iteration 3	8.07-10.4 (2.5 th -97.5 th percentile)	10.1	Yes	21.8	No
All records	19.94-24.5 (2.5 th -97.5 th percentile)	24.3	Yes	53.7	No

Results of these validation tests illustrate the importance of model calibration, especially when the water depth is the only hydraulic parameter taken into account (Cammerer et al., 2013; Chang et al., 2008; McBean et al., 1986). In other words, flood damage, being a complicated process, could be dependent on more damage-influencing parameters than those considered here (Fuchs et al., 2011; Grahn and Nyberg, 2014; Hasanzadeh Nafari et al., 2016c; Merz et al., 2013; Schröter et al., 2014). However, when the loss function is calibrated with an actual damage dataset and an empirically based model is provided, the function estimations are good (i.e. low predictive error, low variation, and acceptable reliability in results), and its performance is validated for use in flood events with the same geographical conditions (i.e. flood characteristics and building specifications) as the area of study (Hasanzadeh Nafari et al., 2016b; McBean et al., 1986).

While the FLF-IT model is shown to be more accurate, there are still some limitations that can be the subject of new research. Model validation in this study was based on random samples which were not independent of the data used for model calibration, and this test does not give information about the transferability of the FLF-IT model. Hence, improvements can be made by considering more influencing factors of hazard, exposure and vulnerability; validation with more actual damage records from other study areas in Italy; and considering other types of structure.

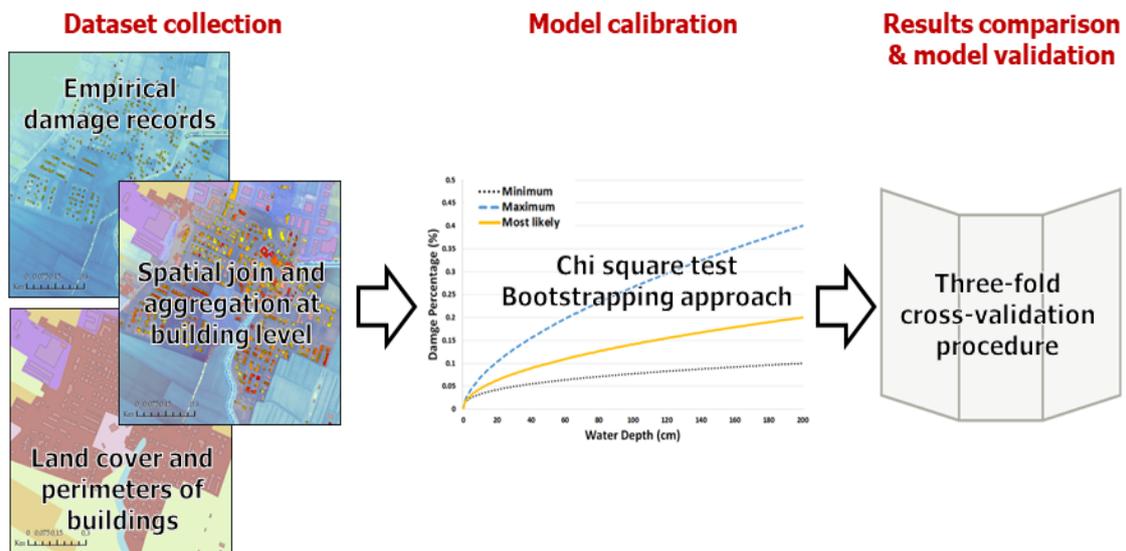


Figure 5-7: Visualisation of the workflow and the methodological steps of the study

5.7 Conclusions

Floods are frequent natural hazards in Italy, triggering significant negative consequences on the economy every year. Their impact is expected to worsen in the near future due to socio-economic development and climate variability. To be able to reduce the probability and magnitude of expected economic losses and to lessen the cost of compensation and restoration, flood risk managers need to be correctly informed about the potential damage from flood hazards on the territory. A loss function that can reliably estimate the economic costs based on available data is the key to achieving this objective. However, despite a significant number of flood disasters hitting Italy every year, few attempts at developing a flood damage model from post-disaster reports have been made.

Flood loss functions are an internationally accepted method for estimating direct flood damage in urban areas. Flood losses can be classified as marketable or non-marketable values and as direct or indirect damages. This study focused on direct, marketable damage due to riverine floodwater inundation. We employed a newly derived Australian approach (FLFA) with empirical damage data from Italy to develop a synthetic, relative flood loss function for Italian residential structures (FLF-IT). The

FLFA approach takes data of damage and depth, stratified by building classifications, and uses the chi-square test of goodness of fit to fix a parameterised function to compute depth-damage estimates. Parameters include the height of the stories, maximum damage as a percentage of the total building value, and the elevation of water at which buildings start being damaged. Additionally, FLFA illustrates a bootstrapping approach to the empirical data to assist in describing confidence limits around the parameterised functional depth-damage relationship. Accordingly, the advantages of the new model (FLF-IT) include calibration with empirical data, consideration of the epistemic uncertainty of data, and the ability to change parameters based on building practices across Italy. After model calibration, its performance was also validated for predicting the loss ratios and absolute damage values. Also, the performance of the new model in comparison to the empirical data has been contrasted with an uncalibrated relative model with frequent usage in Europe. In this regard, a three-fold cross-validation procedure and the usual bootstrap approach were applied to the empirical sample to measure the range of uncertainty from the actual damage data. This validation test was selected to compensate for the lack of comparable data from an independent flood event. Finally, the predictive capability has also been studied for some sub-classes of water depth. The validation procedure shows that estimates of FLF-IT are good (no bias, 10% mean absolute error, and 14% root mean square error), especially when the flood is deep, and its performance is acceptable. However, the application of the Damage Scanner model using the original uncalibrated maximum damage values leads to overestimating the actual damage that occurred during this flood event.

Results of these validation tests depict the importance of model calibration, especially when the water depth is the only hydraulic parameter considered. In other words, when the loss function is calibrated and an empirically based model is provided, the function performs well (i.e. low predictive error, low variation, and acceptable reliability), and its performance is validated for use in events with the same geographical conditions as the area of study. Awareness of these issues is necessary for decision-making in flood risk management. Further research will be aimed at considering some additional parameters

that may govern the significance of the damages for a given depth. An independent dataset is required to evaluate the predictive capacity and transferability of the model.

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6 AN ASSESSMENT OF THE EFFECTIVENESS OF TREE-BASED MODELS

FOR MULTI-VARIATE FLOOD DAMAGE ASSESSMENT IN
AUSTRALIA [Published Chapter]⁴

6.1 Abstract

Flood is a frequent natural hazard that has significant financial consequences for Australia. In Australia, physical losses caused by floods are commonly estimated by stage-damage functions. These methods usually consider only the depth of the water and the type of buildings at risk. However, flood damage is a complicated process, and it is dependent on a variety of factors which are rarely taken into account. This study explores the interaction, importance, and influence of water depth, flow velocity, water contamination, precautionary measures, emergency measures, flood experience, floor area, building value, building quality, and socioeconomic status. The study uses tree-based models (regression trees and bagging decision trees) and a dataset collected from 2012 and 2013 flood events in Queensland, which includes information on structural

⁴ Hasanzadeh Nafari, R., Ngo, T., Mendis, P., 2016. An Assessment of the Effectiveness of Tree-Based Models for Multi-Variate Flood Damage Assessment in Australia. *Water* 8, 282.

damages, impact parameters, and resistance variables. The tree-based approaches show water depth, floor area, precautionary measures, building value, and building quality to be important damage-influencing parameters. Furthermore, the performance of the tree-based models is validated and contrasted with the outcomes of a multi-parameter loss function (FLFARs) from Australia. The tree-based models are shown to be more accurate than the stage-damage function. Consequently, considering more parameters and taking advantage of tree-based models is recommended. The outcome is important for improving established Australian flood loss models and assisting decision-makers and insurance companies dealing with flood risk assessment.

6.2 Introduction

In recent decades, flood risk is growing, due to climate change and increase in vulnerability of properties at risk (Elmer et al., 2012; Hasanzadeh Nafari et al., 2016a; Kundzewicz et al., 2005). In Australia, floods are the most costly of all disaster types (Box et al., 2013), contributing 29% of the total cost of the nation's economy and the built environment (Bureau of Transport Economics, 2001; Hasanzadeh Nafari et al., 2016b). Accordingly, flood risk management is attracting more attention (Kreibich et al., 2010; Schröter et al., 2014; van Ootegem et al., 2015), and results are used to inform disaster management policy and support the development of risk reduction measures (Emanuelsson et al., 2014; Merz et al., 2010). Flood risk management has to be based upon an appropriate evaluation of flood hazard and flood vulnerability (Chen et al., 2016; Olsen et al., 2015), including an assessment of damage and effectiveness of risk reduction measures (Bubeck et al., 2016; Merz et al., 2013; Morita, 2014). Therefore, loss estimation and consequence assessment is an indispensable part of flood risk management (de Moel et al., 2015; Handmer et al., 2005). However, compared to the available methods and information on flood hazard, flood damage models are still crude, and understanding of the damage process is largely unknown (Gall et al., 2009; Gerl et al., 2014; Merz et al., 2013, 2010).

Flood losses can be grouped into four different classifications: direct tangible, direct intangible, indirect tangible, and indirect intangible damages (Wind et al., 1999). The direct classification takes place due to physical contact with flooded objects, but the indirect category is induced by the direct damage on a wider scale of space and time (Jonkman and Dawson, 2012; Meyer et al., 2013; Thielen et al., 2005). Tangible losses can be quantified financially, while intangible losses cannot (André et al., 2013; Kreibich et al., 2010). The existing methods for flood damage assessment are commonly focused on direct tangible damages of residential, industrial, agricultural, and commercial sectors. However, residential buildings are usually more affected by floods (Chinh et al., 2015). Consequently, the focus of this study is on direct, tangible damage to residential building structures after a short inundation.

Stage-damage functions are the international standard of flood loss assessment (Cammerer et al., 2013; Hasanzadeh Nafari et al., 2016a; Thielen et al., 2006). The simplicity of stage-damage functions is the main reason for their common usage. However, studies have shown that they might be subject to significant uncertainties since some influencing parameters are neglected in their damage assessment (Chinh et al., 2015; Merz et al., 2013). Flood damage is a complicated process and is dependent on a variety of parameters. These can be classified into impact parameters (e.g. flood depth, flood duration, flow velocity, water contamination, and return period) and resistance parameters (e.g. building characteristics, private precaution, early warning, emergency measures, flood experience, and socioeconomic status) (Thielen et al., 2005). These parameters may not be independent of each other, and their single or joint effects are widely unknown (Merz et al., 2013). However, the majority of flood damage models have attempted to propose simplified approaches based on the type or use of elements at risk and the inundation depth of water (Schröter et al., 2014). Consequently, using these models might increase the uncertainty of results, particularly when they are employed in study areas other than the area of origin (Cammerer et al., 2013; Chang et al., 2008; Hasanzadeh Nafari et al., 2016b; McBean et al., 1986).

Nonetheless, there are some exceptions. Wind et al. (1999); Penning-Rowsell and Green (2000); Smith (1994); and Parker et al. (2007) studied the effects of early warning time and preparedness on the magnitude of flood damages (Merz et al., 2013; Parker et al., 2007; Penning-Rowsell and Green, 2000; Smith, 1994; Wind et al., 1999), and some multi-parameter models have recently been developed for quantifying the single or joint effects of influencing parameters (Chinh et al., 2015). For instance, in the UK, a conceptual model has been drawn up to suggest the critical parameters that should be considered in flood loss assessment, albeit without discussing the weight of contributions or the importance of parameters (Merz et al., 2013; Nicholas et al., 2001). In Japan, a multi-variate model has been developed by Zhai et al. (2005), although the performance of the model has not been validated or compared with other flood loss models (Merz et al., 2013; Zhai et al., 2005). In Germany, a Bayesian network for flood damage assessment has been developed by Vogel et al. (2013) (Vogel et al., 2013). Another multi-parameter model is related to 2002, 2005 and 2006 flood events in Germany and has been established and developed by Thielen et al. (2005), Kreibich et al. (2005, 2007) and Elmer et al. (2010). This multi-parameter model (FLEMO) has been developed, applied, and validated for private households and companies at both the micro- and meso-scale (Elmer et al., 2010; Kreibich and Thielen, 2008; Kreibich et al., 2010, 2007, 2005; Seifert et al., 2010; Thielen et al., 2008, 2006, 2005). These studies have demonstrated that multi-parameters consideration can improve flood loss modelling in Germany (Merz et al., 2013).

The interaction or influence of different parameters can be explored with a tree-based modelling statistical analysis. This approach has frequently been used by hydrology and water resource researchers. However, it is still novel in the domain of flood-loss modelling. Merz et al. (2013) have recently analysed the FLEMO flood loss model dataset with a tree-based data mining approach. The results of this study revealed that the depth of water, area of buildings, return period of flood, contamination, duration of flooding, and precautionary measures, respectively, have the highest influences on flood loss assessment in the region of study (Chinh et al., 2015; Merz et al., 2013). Also, these analyses show that the tree-based damage model is more accurate than the FLEMO

multi-parameter model. Another study with the same concept has been developed for the city of Can Tho in the Mekong Delta. In this area of study, as opposed to Germany, the flood had a shallow depth with a long duration. Consequently, inundation duration, equated with the depth of water, was the greatest influencing factor. In addition to these two parameters, the single or joint effects of 22 more predictors have been evaluated and examined (Chinh et al., 2015).

To our knowledge, the tree-based approach has not been developed and validated for Australia, and we hypothesise that this method would be more accurate than the existing traditional stage-damage functions. The objective of this study is to employ tree-based data mining methods to examine the effect and importance of damage-influencing parameters using a dataset collected from 2012 and 2013 flood events in Queensland. The performance of the tree-based models is also compared with the outcomes of a newly established multi-parameter loss function (FLFA_{rs}) from Australia.

6.3 Study Area and Data

For this study, two areas were chosen. The first survey area is the city of Bundaberg in Queensland, Australia, located in the vicinity of the Burnett River waterway north of the state capital, Brisbane (Figure 6-1). The Burnett River catchment is located in south-east Queensland, with the main system incorporating the rivers of Three Moon Creek, Burnett River, Nogo Creek, Auburn River and the Boyne River, in addition to many other creeks and tributaries. The total Burnett River catchment area is approximately 33,000 square kilometres. This area is bound by the catchments of the Fitzroy and Kolan Rivers to the north; the Dawson and Condamine Rivers to the east and the Brisbane and Mary Rivers to the South. The Burnett River catchment has had a long history of flooding that has impacted both the urban centres and rural areas (North Burnett Regional Council, 2014). The Bundaberg ground elevation and the Burnett River catchment are illustrated in Figures 6-2 and 6-3. In recent years, the city of Bundaberg has experienced some extreme flood events. The most recent flood responses from Bundaberg Regional Council date back to the floods in November 2010,

January 2013, February 2013, and February 2015 (Hasanzadeh Nafari et al., 2016a). During the flood event in January 2013, 200 businesses were inundated, and over 2000 residents and 70 hospital patients were evacuated. Furthermore, the performance of lifelines was disrupted, and infrastructures were impacted (Queensland Government, 2013). This flood event that occurred from 21–29 January 2013 was a result of the Tropical Cyclone Oswald, and the associated rainfall and flooding had a catastrophic effect on Queensland and it is considered to be the worst flood experienced in Bundaberg’s recorded history. The height of the floodwaters in Bundaberg city from Burnett River reached 9.53 metres at its peak, and over 2000 properties were affected (Hasanzadeh Nafari et al., 2016a). The extension of the water depth is illustrated in Figure 6-4. Bundaberg Regional Council estimated that the public infrastructure damage from the flood event of 2013 was approximately AUD 103 million (Hasanzadeh Nafari et al., 2016a). The second study area is the city of Roma, located on Bungil Creek, a tributary of the Condamine River in the Maranoa region in Queensland (Figure 6-5). The flood event in 2012 is considered to be the worst flood experienced in Roma’s history, having inundated 444 homes. This flood event that occurred from late January to early February 2012 was a result of heavy rainfall. The boundary of the flood is illustrated in Figure 6-6. The Maranoa Regional Council estimated that the public infrastructure damage from the natural disaster events of 2012 was approximately AUD 50 million (Hasanzadeh Nafari et al., 2016a). The return periods of both flood events have been estimated to be approximately 100 years, based on the flood frequency analyses (North Burnett Regional Council, 2014).

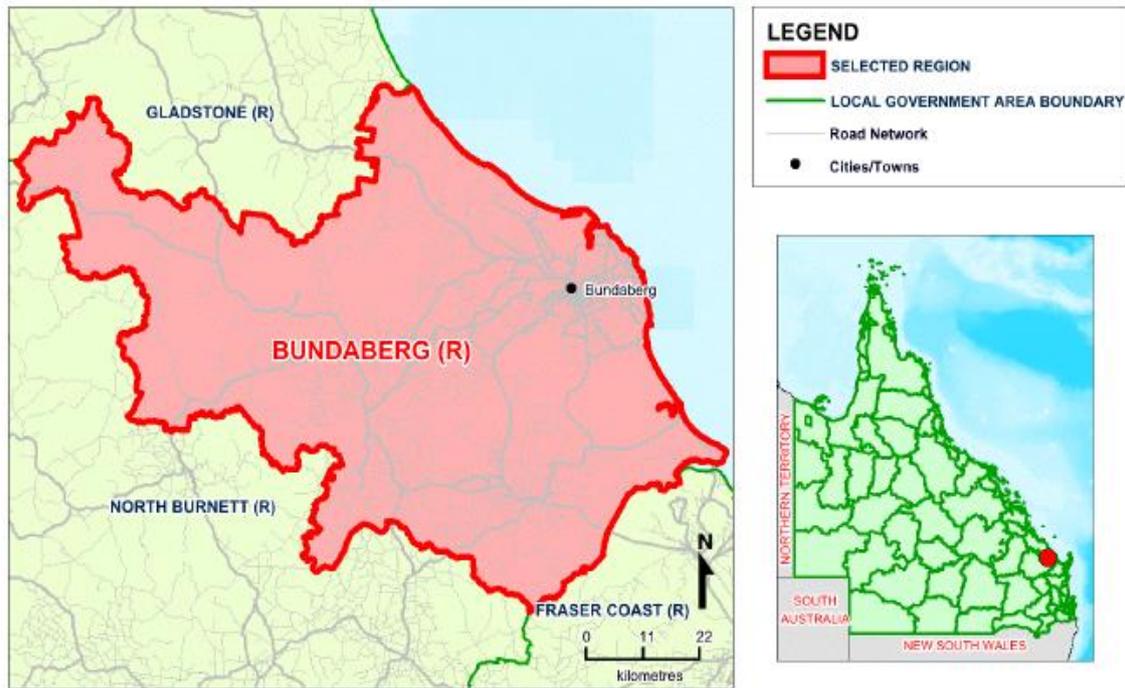


Figure 6-1: Map of Bundaberg Regional Council (Queensland Government, 2011a)

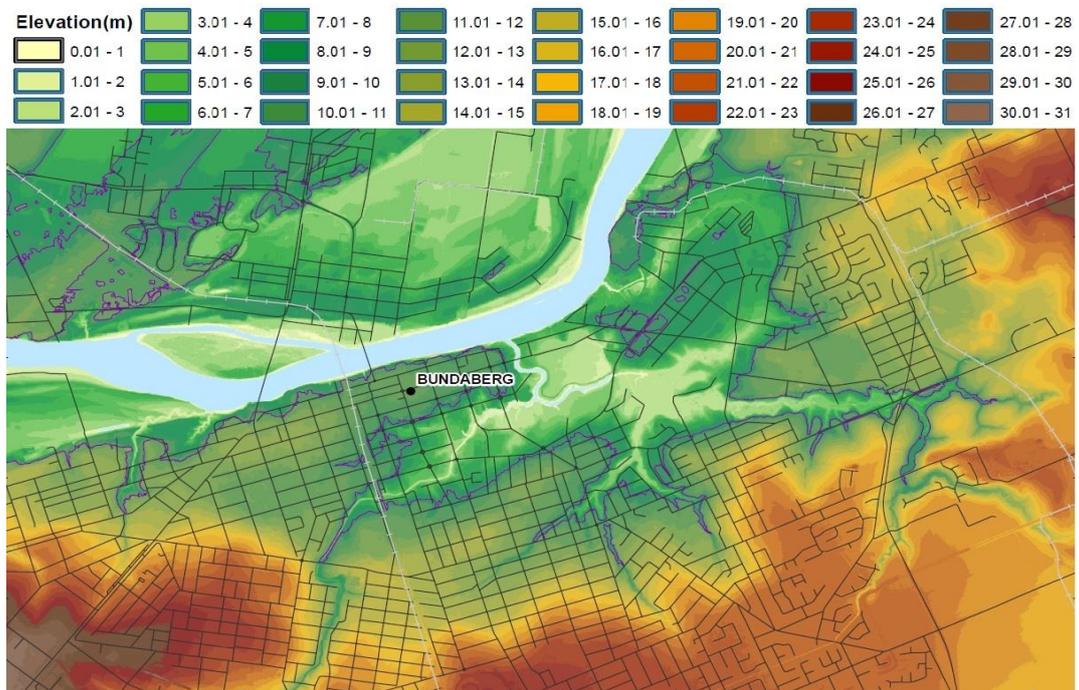


Figure 6-2: Bundaberg ground elevation (Bundaberg Regional Council, 2013a)

Chapter 6: An Assessment of the Effectiveness of Tree-based Models

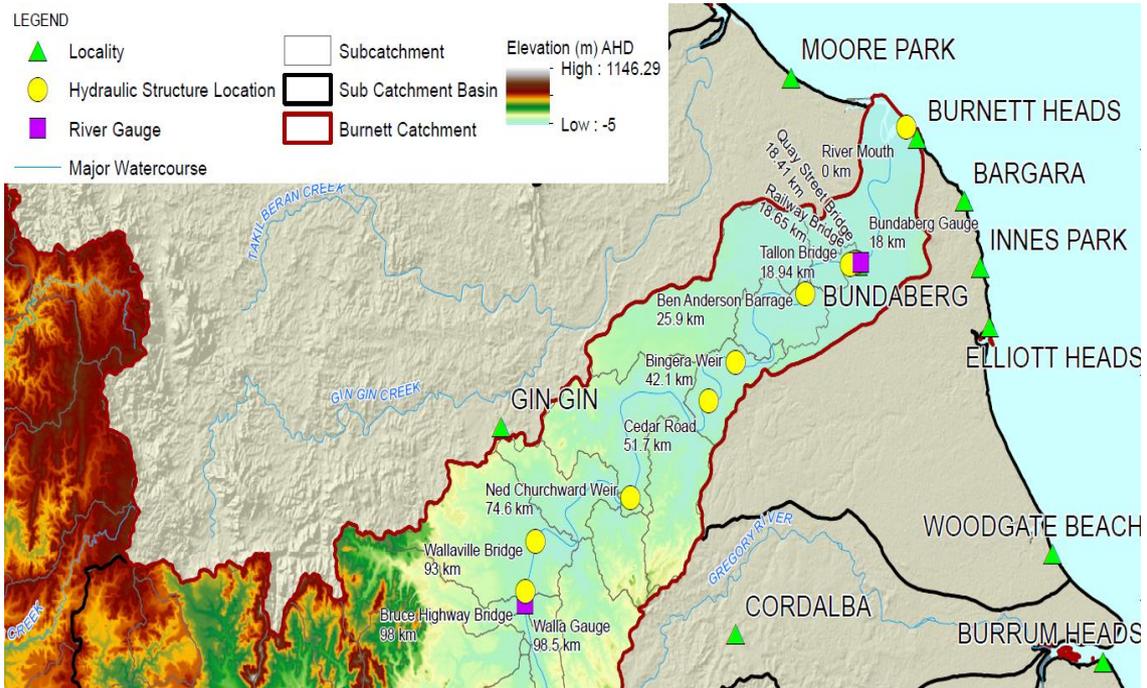


Figure 6-3: A part of the Burnett River catchment related to the area of the study (Bundaberg Regional Council, 2013b)

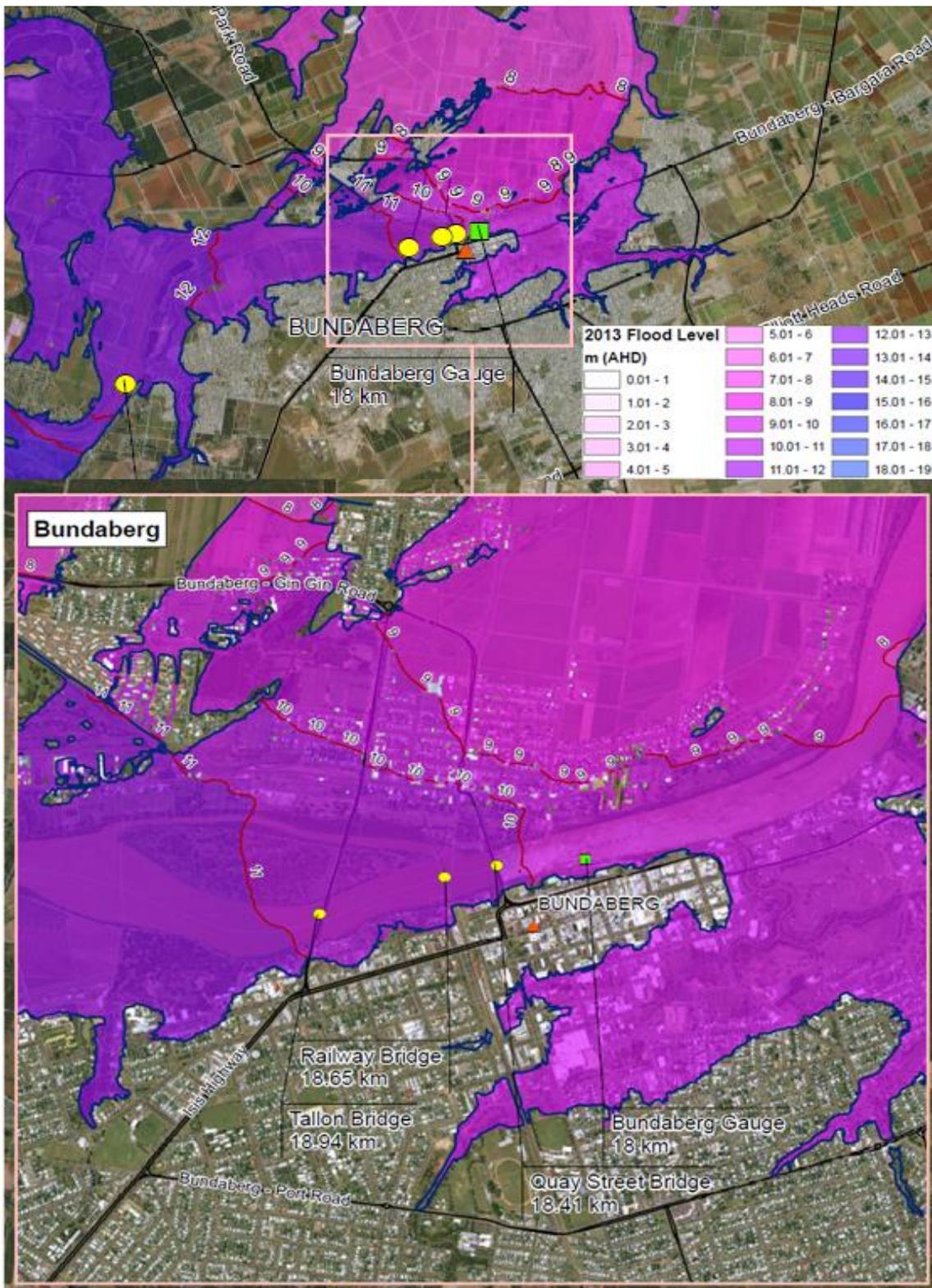


Figure 6-4: Inundation map of 2013 flood (Bundaberg Regional Council, 2013c)

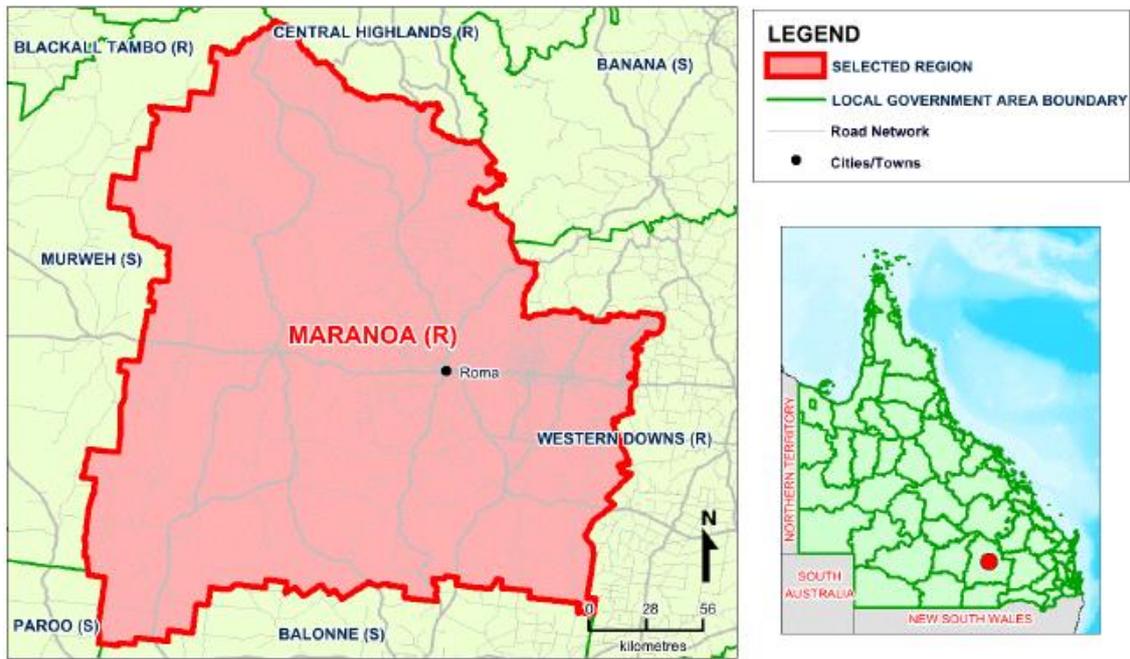


Figure 6-5: Map of Maranoa Regional Council (Queensland Government, 2011b)

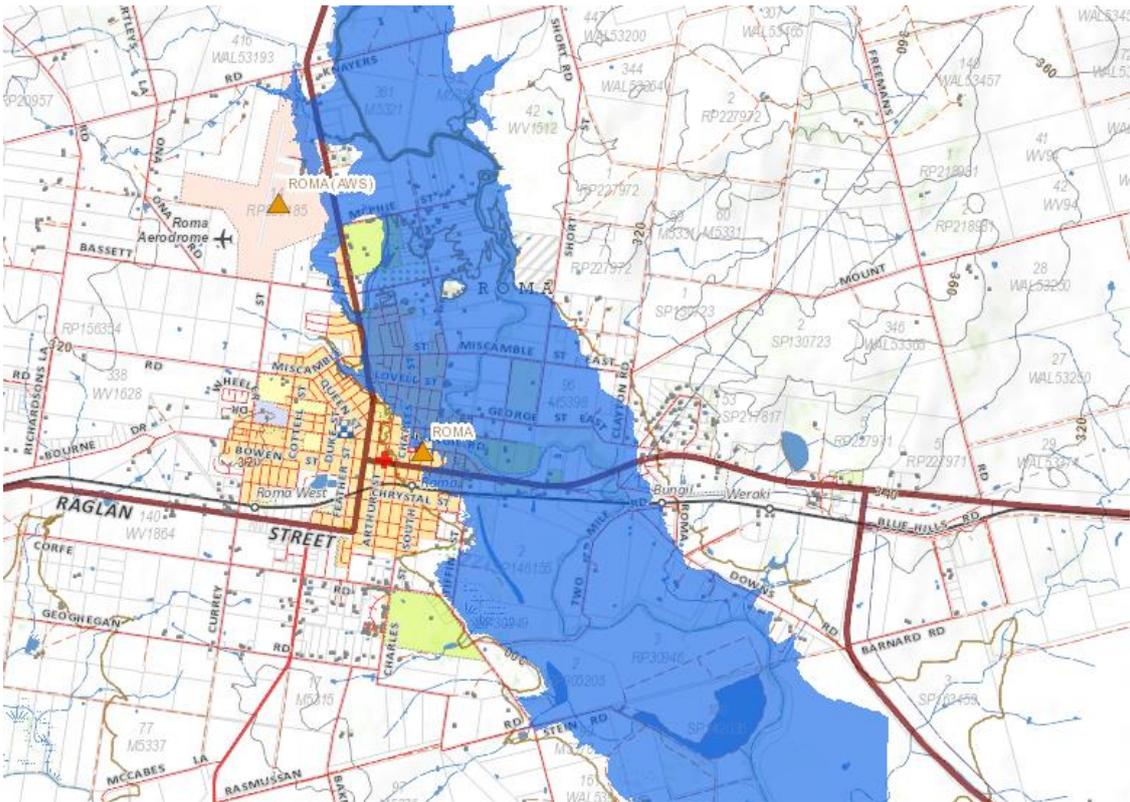


Figure 6-6: Boundary of the 2012 historic flood event (Qld Department of Natural Resources and Mines, 2015)

The empirical dataset used for this study (457 loss cases from the 2013 flood and 150 loss cases from the 2012 flood) was gathered after these two flood events from the Queensland Reconstruction Authority, a governmental responder organisation to Queensland disaster events. The official dataset—which was collected by either two or three post-disaster on-site surveys based on a standardised procedure and unified guidelines of the survey—provides data on the intensity of hazard (i.e. water depth, information on water contamination, and information on flow velocity), characteristics of buildings (i.e. material, floor space, construction type, number of building storeys, information on utilities and solar panels, and emergency measures undertaken), and the magnitude of losses. It is worth mentioning that for every building, the magnitude of damage has been explained based on the affected structural components. Accordingly, based on the average value of damaged items relative to the total value of the structure, the descriptions of damages have been exchanged into a percentage of damages (Hasanzadeh Nafari et al., 2016a). Further complementary data (e.g. building age, length of residency, average replacement building value, the number of residences, and socioeconomic status) was collected from the National Exposure Information System of Australia (Dunford et al., 2014). Consequently, the final dataset provides 20 attributes on 607 inundations. Candidate predictors are either extracted directly from one attribute (e.g. water depth or building area) or transformed from several attributes (e.g. building quality or flow velocity). Data preparation and data transformation are discussed further below.

- **Water depth and water contamination:** this information was collected in two post-disaster surveys. The value of water depth fluctuated between 0 cm and 700 cm above ground. However, for 96% of buildings, this attribute was equal to or less than 350 cm. Also, the existence of sewage, biological, or chemical contamination has been checked and reported by visual inspection and smell. Accordingly, water contamination was ranked based on the reported material and the existing chemical hazards, from 0 (no contamination) to 2 (chemical contamination), with 1 representing only sewage contamination.

- Flow velocity: flow velocity was assessed according to the comments of inspectors about the amount of water penetration inside of buildings, the volume of deposited materials, and the type of sediment next to the house (mud, sand, gravel or stone). Afterwards, this information was transformed and ranked as calm (1: no deposit or only mud sediment), medium (2: sand sediment or a considerable amount of water penetration), or high (3: gravel or stone sediment or high volume of deposits) flow velocity.
- Emergency measures: the dataset provides information about whether or not people undertook any action against water infiltration, e.g. pumping water out or cut-off of electricity supply. Subsequently, these actions were ranked from 0 (no measure was undertaken) to 3 (many measures were undertaken), with 1 representing that only water was pumped out, and 2 representing that only electricity supply was cut off. The “cut-off of electricity supply” measure had a greater weight due to the high value of electrical equipment (Hasanzadeh Nafari et al., 2016a).
- Precaution measures: the indicators of precaution measures were defined and ranked based on the construction type (3: high-set open under, 2: low-set with suspended floor, or 1: high-set enclosed under or slab on ground); protection of utilities and power system against water impacts (1: no protection, 2: protected); availability of solar-panel power provider (1: not available, 2: available); and the number of building storeys (1: one-storey buildings, 2: two-storey buildings). Eventually, precaution measure indicators were calculated and weighted by multiplying the above ranks.
- Flood experience: the areas of study have experienced a variety of flood events in recent years (Hasanzadeh Nafari et al., 2016a; Honert and McAneney, 2011). Therefore, this parameter has been assessed and averaged according to the length of residency. Overall, about 11% of households moved into the areas one year or less before the events, weighted 1. About 31% of families settled there in the last five years, weighted as 2. Residents with more than five years length of residency were weighted 3.

- **Building quality:** this item is a function of age (i.e. constructed pre- or post- 1981) and material (e.g. timber, brick, concrete, or metal) of buildings. Age of buildings was weighted 1 if the structure was constructed pre-1981 and 2 if it was constructed post-1981. Also, the resistance of different materials against impacts of water is judged and ranked: 1 for timber, 2 for brick, and 3 for concrete or metal, according to the Australian building guidelines for flood prone areas (Hawkesbury-Nepean Floodplain Management Steering Committee, 2006). Finally, this candidate predictor is defined by multiplying the weight of age by the weight of the material.
- **The value and floor space of building:** for every building, the value was calculated by multiplying the total area reported by the inspectors by the average replacement value per square metre extracted from the national exposure information system of Australia (Dunford et al., 2014). In this study, besides considering the area of the buildings, the contribution of the residents' density with the extent of losses has been taken into account. Accordingly, floor space of the building was calculated per person, by dividing the total area by the number of residents.
- **Socioeconomic status:** this category includes information about ownership status and monthly income (i.e. low: \$1–\$599, middle: \$600–\$1999, or high: greater than \$2000). Also, it represents buildings whose residents need special attention (i.e. aged less than five or more than 65; needing assistance with a core activity; or do not speak English well) or low education residents (i.e. the highest educational attainment of all building residents is year 11 or below).

Following the approach of Merz et al. (2013) and Chinh et al. (2015), these predictors were classified into five main categories: (1) flood impact; (2) emergency measures; (3) precaution and flood experience; (4) building characteristics; and (5) socioeconomic status (Table 6-1). Table 6-2 shows the Pearson correlation coefficient of the final candidate predictors and the loss ratio. As expected, and as other researchers have claimed (Hasanzadeh Nafari et al., 2016a; Merz et al., 2013; Thielen et al., 2005), water depth has the highest absolute correlation with loss ratios (Figure 6-7). However, many other variables—such as flow velocity, contamination, precaution measure, floor space

per person, the value of the affected building, and building quality—are also significantly correlated to damage ratio.

Table 6-1: Description of the 13 candidate predictors (C: continuous, O: ordinal, N: nominal)

Categories	Predictors	Type	Range	
Flood impact	WD	Water depth	C	between 0 cm and 700 cm above ground
	Vel.	Flow velocity	O	1 = calm to 3 = high
	Con.	Water Contamination	O	0 = no contamination to 2 = heavy contamination
Emergency	EM	Emergency Measures	O	0 = no measure undertaken to 3 = many measures undertaken
Precaution, experience	PM	Precaution Measures	O	1 = no measure undertaken to 4 = many measures undertaken
	Exp.	Flood experience	O	1 = few flood experience to 3 = recent flood experience
Building characteristic	BQ	Building quality	O	1 = very bad to 6 = very good
	BV	Building value	C	1756 to 3594000 AUD
	FS	Floor space per person	C	13 to 870 m ²
Socioeconomic status	SA	Special attention resident	N	0 = No, 1 = Yes
	Own.	Ownership status	N	0 = rent, 1 = own
	Inc.	Monthly income	O	1 = \$1–\$599, 2 = \$600–\$1999, 3 = greater than \$2000
	LE	Low education residents	N	0 = No, 1 = Yes

Table 6-2: Pearson correlation of the 13 final candidate predictors (see Table 6-1) and loss ratio. Significant correlations (5% significance level) are marked bold

Loss Ratio	Pearson Correlation Coefficient												
	WD	Vel.	Con.	EM	PM	Exp.	BQ	BV	FS	SA	Own.	Inc.	LE
	0.62	0.23	0.19	-0.05	-0.16	-0.03	-0.07	-0.14	-0.15	0.04	-0.03	-0.04	0.02

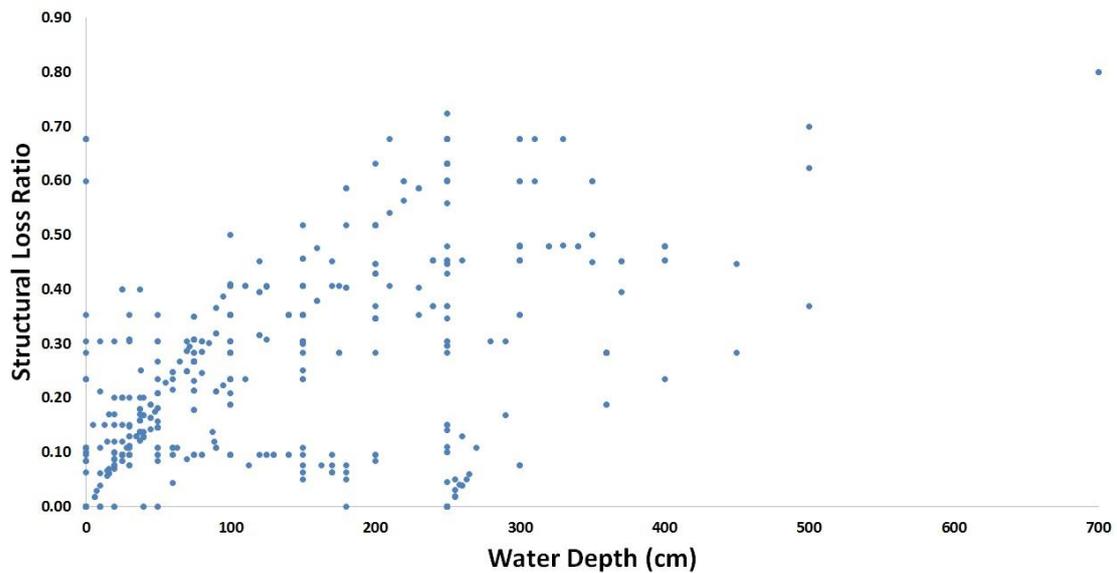


Figure 6-7: Scatter plot showing the relation between loss ratio and water depth (structural loss ratio does not cover the damages of mobile contents, and it is only limited to all building fabrics including stationary interiors)

6.4 Statistical Methods

Regression trees and bagging decision trees were applied to determine the prominent damage-influencing parameters, to understand their effect on the extent of structural damage, and to compare the performance of the tree-based models with an established flood loss function. The tree-based analyses were performed with the Weka machine learning software (Kalmegh, 2015).

6.4.1 Regression Trees

Regression trees are machine learning methods for constructing prediction models from data where the target variables are continuous values (Loh, 2011). Tree-based regression models are known for their simplicity and efficiency when facing up to domains with a large number of variables and data (Buja and Lee, 2001). They are constructed by sub-dividing the predictor data space into smaller areas such that in each split, the dataset is partitioned into two sub-spaces. In this regard, each terminal node is labelled with a question and the binary branches are labelled with the answers.

Subdivision should be performed in such a way that the predictive accuracy is maximised, and errors are minimised. In other words, the algorithm searches over all possible split values of all predictor variables to identify the split which minimises an error criterion. Overall, trees should be complicated enough to take advantage of information that increases predictive power, while simple enough to ignore random noises that do not enhance the accuracy of results (Merz et al., 2013).

If a decision tree model is fully grown, it may lose some generalisation capability, and if the training data contains any errors, it can lead to poor performance on unforeseen cases. This issue is known as overfitting and needs careful attention (Breiman et al., 1984; Pal and Mather, 2003). One way to avoid overfitting is tree pruning, which was employed in this study. Tree pruning is a technique in machine learning that decreases the size of decision trees by taking off sections of the tree that give little power to classify instances. Pruning reduces the complexity of the final classifier and hence improves predictive accuracy by the reduction of overfitting (Bramer, 2007).

In this study, the target variables were relative structural loss values and trees were constructed using the entire dataset. Therefore, some repeated binary partitioning questions construct the structure of the tree, from the root node to the terminal nodes (or leaves). Terminal node values give the average loss ratio of all data values of the terminal node (Merz et al., 2013). In other words, the prediction of loss ratio is the average of the training dataset that belongs to every leaf.

The prediction error used for Figure 6-8 is estimated by a 10-fold cross-validation technique based on the average absolute deviation of the estimated ratios from the observed values (MAE). In this regard, the shuffled data was first partitioned into 10 equally-sized segments (folds). A tree was computed 10 times. In each iteration, a different fold of the data was held out for model testing while the remaining nine folds were used for model training. Eventually, the error was averaged over all constructed models (Hasanzadeh Nafari et al., 2016b; Refaeilzadeh et al., 2009).

6.4.2 Bagging Decision Trees

The bagging predictor is a method for generating a multiple version of a predictor and using this to get an aggregated predictor. The multiple version is formed by making bootstrap replicates of the entire dataset and using each replica to grow a new regression tree. The response of a bagging decision tree is the average of all individual regression trees. Bootstrapping and ensemble models make the response strong enough to cope with variation in data and avoid the overfitting issue. Tests on real and simulated datasets using regression trees have shown that compared to an individual regression tree, bagging can substantially enhance the stability and accuracy of the model's performance (Breiman, 2001, 1996; Elghazel and Aussem, 2013; Machová et al., 2006; Merz et al., 2013). About one-third of data is not used for training the individual regression trees. This segment, called out-of-bag data, is the observation data utilised for error estimation and feature importance assessment.

The quality of a bagging tree, used for exploring the feature importance, is measured by the average error of predictions of all regression trees compared with the observation data (out-of-bag data). In this regard, the values of one variable in the out-of-bag examples is randomly permuted, and the increase in the out-of-bag error is measured: the greater the growth, the more important the feature (Breiman, 2001; Chinh et al., 2015; Merz et al., 2013).

6.4.3 Comparing the Performance of the Tree-Based Models with FLFArs

The tree-based models constructed in the previous stages, based the on the entire dataset, were utilised for loss ratio estimation and comparison with the stage-damage function. For a meaningful comparison, all models should be derived from the same dataset (Merz et al., 2013). Accordingly, the performance of the tree-based model was compared with a newly established multi-parameter flood loss model (FLFA_{rs}) (Hasanzadeh Nafari et al., 2016a), which has been derived from the same flood event data.

The results of the damage models have been compared with the following resampling procedure. First, 100 samples are randomly pulled out from the original data set, and each model is implemented with this random sample. Errors in the estimates from the aforementioned models in contrast to the actual values are evaluated by three error measures: mean absolute error (MAE), root mean square error (RMSE), and correlation coefficient. Then, this step is repeated 200 times and the average of errors converged to a final constant value. Finally, the performance of the damage models is compared according to the converged values of the averaged errors (Figure 6-11).

6.5 Results and Discussion

6.5.1 Importance and Interaction of the Damage Influencing Parameters

Regression Trees

Regression trees were created in different sizes. Figure 6-8 compares the various trees based on the cost error parameter. The largest tree was stopped with 19 terminal nodes (Figure 6-9). As stated before, trees should be complicated enough to take advantage of information that increases predictive power, while simple enough to ignore random noises that do not enhance the accuracy of results (Merz et al., 2013). Accordingly, after using tree pruning technique for all sizes of regression trees, the tree with 19 terminal nodes and a minimum value of error (0.0652) was selected. In this tree, five predictors out of the 13 candidates were considered and correlated with loss ratios. Table 6-3 shows how many times these predictors were used in decision nodes and how these parameters are correlated with loss ratios. A positive correlation means that the loss ratio increases or decreases as the candidate predictor increases or decreases, and the reverse for a negative correlation.

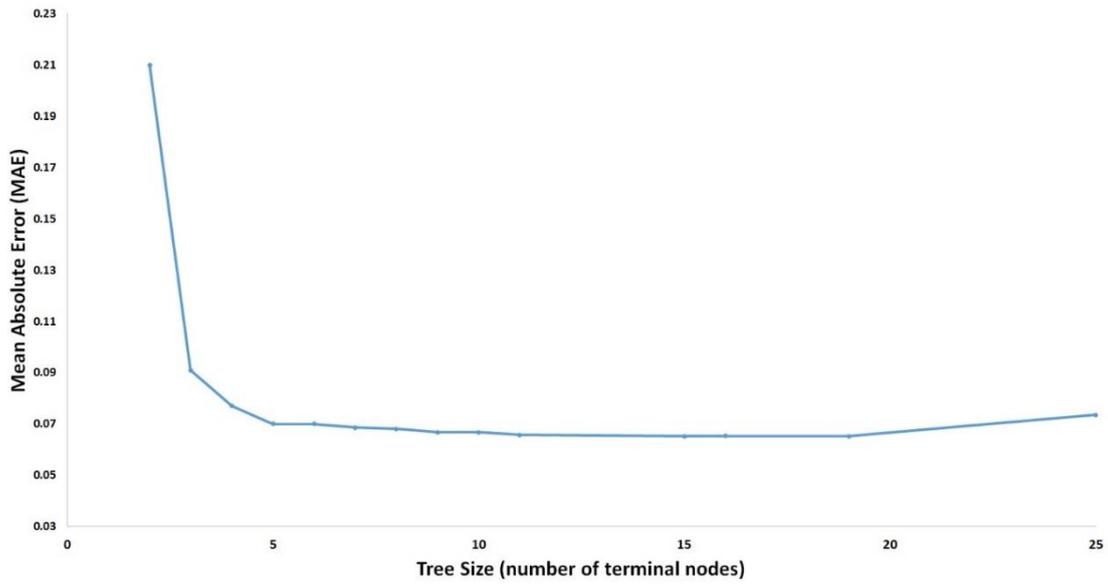


Figure 6-8: Comparison of various pruned regression-trees, based on the mean absolute error (MAE) calculated by a 10-fold cross-validation technique

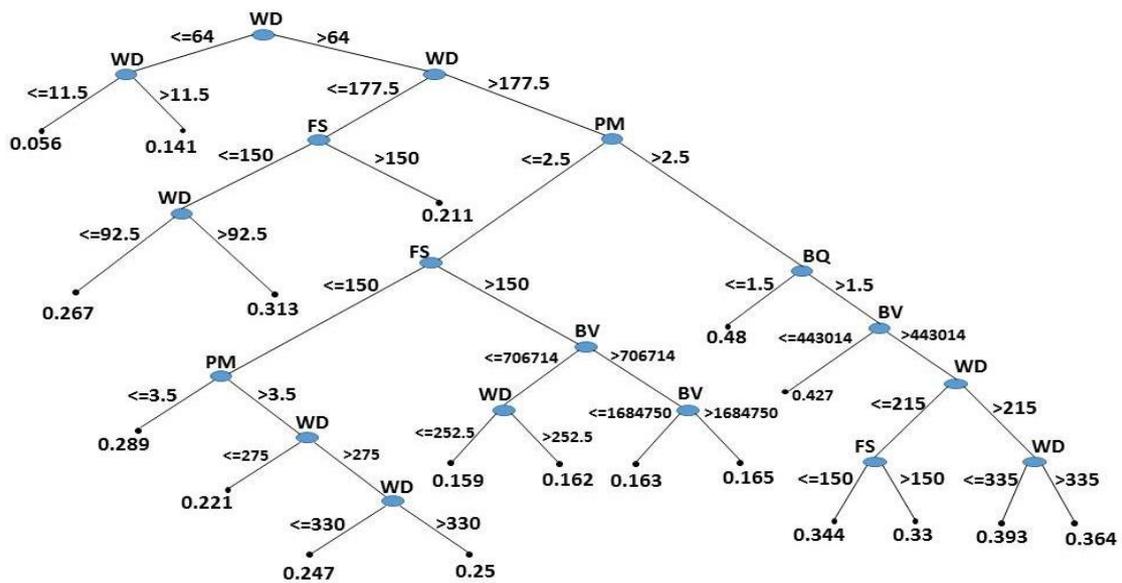


Figure 6-9: Regression tree with 19 leaves for estimating the structural loss ratios (WD: water depth, FS: floor space, PM: precaution measures, BV: building value, BQ: building quality)

Table 6-3: Damage-influencing variables of regression tree with 19 leaves

Candidate Predictors	No. of Decision Nodes	Correlation with Loss Ratio
Water depth	9	+
Floor space	3	-
Precaution measures	2	-
Building value	3	N.A.
Building quality	1	-

Water depth is the most significant predictor, available in nine decision nodes and correlating positively with the loss ratio. This outcome is as expected, and accords with previous research (Merz et al., 2010; Penning-RowSELL and Green, 2000). After water depth, floor area (space area per person) is the most important influencing factor, correlating negatively with loss ratio. The space area might be substantial if the depth of water is greater than 64 cm. This result accords with the findings of ThiEken et al. (2005) and Merz et al. (2013), who showed that the building loss ratio decreases if the total floor space of the building exceeds 139 m² or 120 m² (Merz et al., 2013; ThiEken et al., 2005). However, in this study, the area of the building reduces the extent of losses if it exceeds 150 m² per person (Figure 6-9).

Another important factor that correlates negatively with the extent of losses is the precautionary measures. In the pruned tree with 19 leaves, the precautionary measures are important only for larger water depths (>177.5 cm). This outcome is opposite to the results of the studies in Germany, where the effects of the precautionary measures were significant only for shallow water depths (Kreibich et al., 2005; Merz et al., 2013). This matter can be explained according to the flood characteristics and the precaution measures considered. As stated, in this study, water depth was the most significant impact factor. On the other hand, the construction type (i.e. how much the first floor has been raised up) and the number of building storeys had the most influential effects on the weighting of the precautionary measures. Accordingly, when the flood depth is shallow, and hazard has little impact, these measurements do not significantly affect the calculated extent of losses. However, when the impact of the flood (water depth) is considerable, precautionary measures—either by substantially decreasing the water

depth on the floor of the building, or by protecting the building fabrics placed at higher levels—will remarkably reduce the extent of losses.

As with precautionary measures, building quality has an inverse effect on the structural loss ratios if the water depth is greater than 177.5 cm. This accords with the above finding that water depth is the greatest influencing factor of the floods, and the resistance parameters are meaningful if the depth of water (hazard impact) is significant. The building value indicator was also presented in three decision nodes of the right part of the tree. Nonetheless, its correlation with the loss ratio is not clear. In other words, on this dataset and in large flood depths, variation in the building value does not have a defined relationship with the trend of the loss ratio. This can be interpreted as a weak local correlation between this predictor and the loss ratio, or as an inherent uncertainty in the data.

Water contamination and flow velocity were not found to correlate with the loss ratios. This result confirms the outcome of Kreibich et al. (2009) and Merz et al. (2013), who showed that the effects of the flow velocity and the water contamination are significant only if the depth of water is shallow and the level of energy head is low (Kreibich et al., 2009; Merz et al., 2013). Since in this study these predictors are reported simultaneously with large flood depths, they do not have a major effect on the extent of the damage. Other defined indicators such as emergency measures, flood experience, and socioeconomic status do not have an evident meaningful relationship with the loss ratios, although these parameters (e.g. water contamination, flow velocity and socioeconomic status) might be related to the loss ratios if an unpruned tree was grown on the dataset. As stated, although unpruned trees might have better performance on the original data, overfitting phenomena could affect their performance for an independent dataset. Accordingly, the authors have not developed unpruned trees for this part of the study. Furthermore, due to the joint effects of parameters, the interaction of emergency measures should also be discussed in the context of warnings and alerts issued during the event.

Bagging Decision Trees

As mentioned earlier, the bagging decision tree is formed by making bootstrap replicates of the entire dataset and using each replica for growing a new regression tree. This step was completed up to 200 times until the average of the ensemble errors became stable. Afterwards, the feature importance and the ranking of the predictors were calculated based on the results achieved from random permute. The grading of the predictors is water depth, space area per person, precautionary measures, building value, building quality and flow velocity (Figure 6-10). Other candidates show slight feature importance. This ranking is very similar to the results obtained from the regression trees, see Table 6-3.



Figure 6-10: Out-of-bag feature importance for bagging decision trees

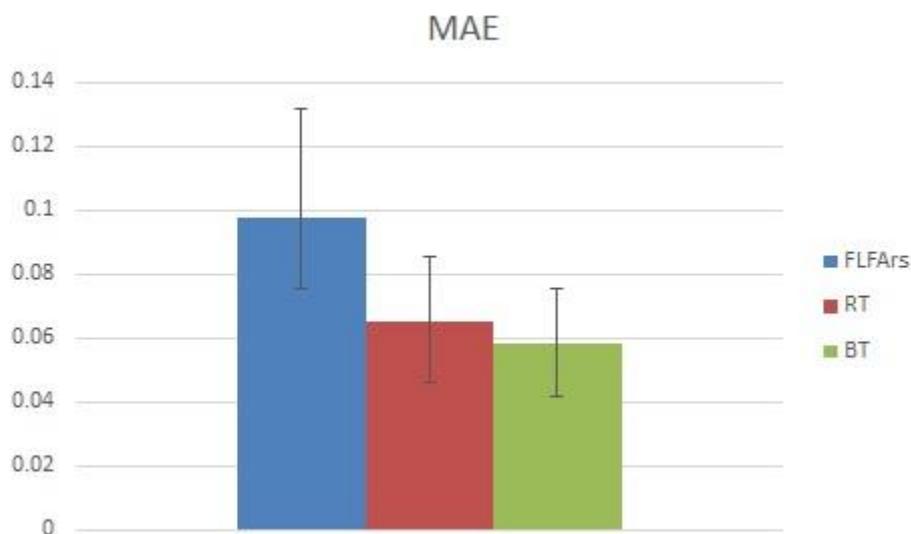
Performance of the Applied Damage Models

In this part of the study, the performance of the tree-based models was compared with FLFA_{rs} multi-parameter flood loss function. As mentioned before, both approaches (the tree-based models and the stage-damage function) were derived based on the same dataset.

Chapter 6: An Assessment of the Effectiveness of Tree-based Models

To compare the performance of the tree-based models with FLFA_{rs}, 200 sets of 100 affected buildings were randomly drawn from the original dataset; each model was applied to every building record and the errors were calculated and averaged over all samples.

Results show that there is a distinct improvement in the tree-based models' performance over the FLFA_{rs} model, which is due to the consideration of more candidate predictors. Also, there is a small improvement in the fulfilment of the bagging decision tree compared to the regression tree. The metrics are the higher value of the correlation coefficients, the lower value of the errors, and the lower variation of the results. This improvement is due to the reduction in the variances of the dataset and the greater accuracy of the model (Figure 6-11). In Figure 6-11, MAE represents the average absolute deviation of the estimated ratios from the observed values and is a quantity used to measure how close the estimates are to the empirical data. The RMSE also expresses the variation of the estimated ratios from the observed ratios. It signifies the standard deviation of the differences between the modelled values and observed values (Chai and Draxler, 2014; Seifert et al., 2010).



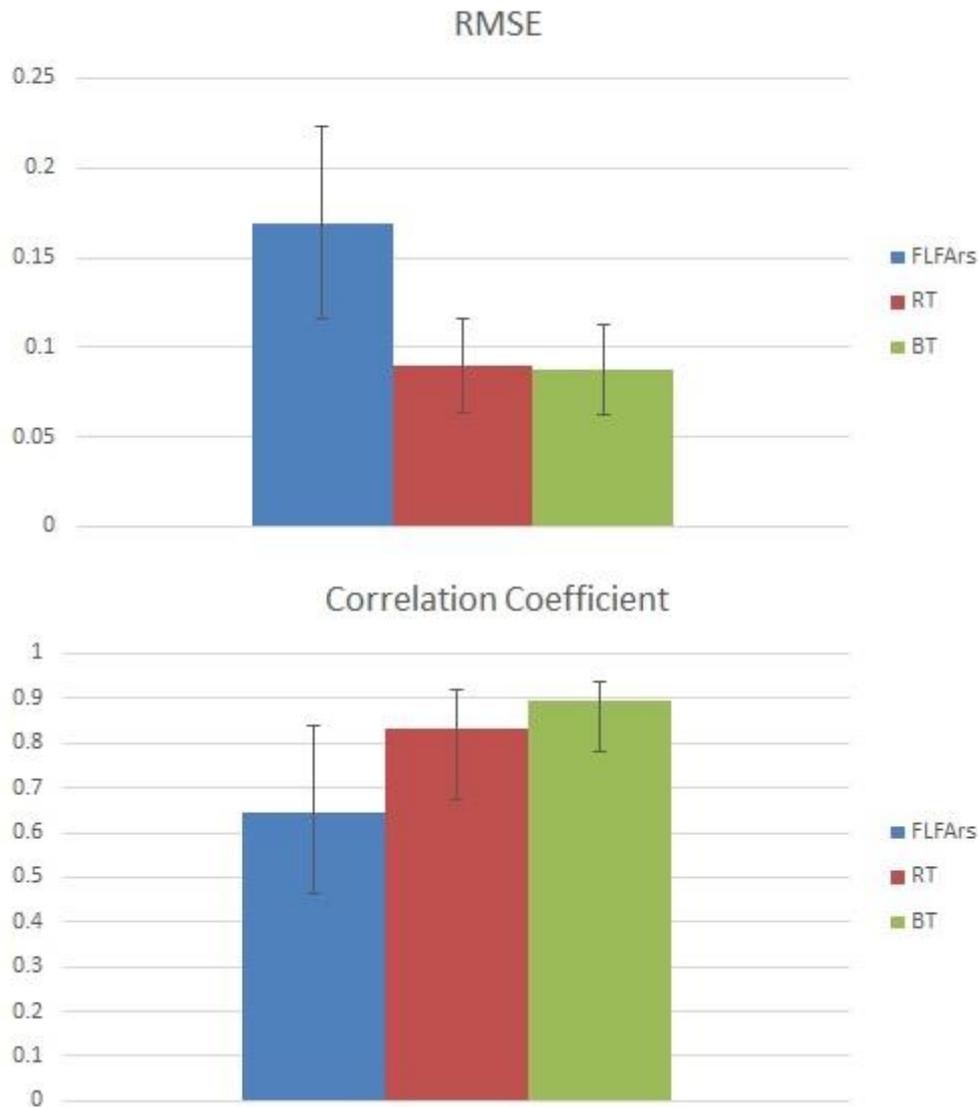


Figure 6-11: Comparison of the flood damage estimation models (FLFArs: Australian stage-damage function, RT: regression tree, BT: bagging decision trees). Bar graphs represent the converged average values of the results, calculated over 200 sets of data samples, and the error bars show the spread of the results

6.6 Conclusions

Flood damage assessment is an important component of flood risk management since inaccurate damage estimation leads to wasted effort, money, and resources for the organisations involved in risk mitigation. The majority of flood damage models have

attempted to propose simplified approaches based on the type or use of elements at risk and the inundation depth of water. However, flood damage is a complicated process, dependent on a variety of factors. Accordingly, the traditional stage-damage functions are subject to significant uncertainties since some influencing factors are usually neglected. If the water depth is the only hydraulic factor considered, the models are not flexible enough to transfer and use in a new area of study. On the other hand, multi-variable models are also subject to uncertainty, particularly since additional variables are taken into account. Therefore, they also entail additional sources of uncertainty. This study used a multi-variate statistical analysis to explore the interaction and effect of many influencing parameters on the extent of flood losses. In this regard, tree-based approaches (e.g. regression trees and bagging decision trees) have been applied, and a dataset collected from 2012 and 2013 flood events in Queensland has been utilised. Previous studies have shown that tree-based models are very effective in identifying the significant damage-influencing parameters and their interactions with the extent of losses since they can extract the local relevance of every predictor. Accordingly, this study has taken advantage of this approach.

The results of the Australian dataset show that water depth is the most significant predictor, correlating positively with the loss ratio. After water depth, floor space per person is the most important influencing factor, correlating negatively with loss ratio. This predictor is substantial if the depth of water is greater than 64 cm and the area of the building exceeds 150 m² per person. Another important factor that correlates negatively with the extent of losses is the precautionary measures. The precautionary measures are important only for large flood depths (>177.5 cm). This outcome is opposite to the results of the studies in Germany, where the effects of the precautionary measures were significant only for shallow water depths. As with precautionary measures, building quality has an inverse effect on the structural loss ratios if the water depth is greater than 177.5 cm. The building value indicator was also presented in three decision nodes of the tree. However, its correlation with the loss ratio is not specified. In this study area, water contamination and flow velocity were not correlated with the loss ratios. Also, it has been shown that socioeconomic status does not play a

fundamental role in flood loss mitigation in the areas of study. As the results of the tree-based approaches show, the following damage-influencing parameters are important: water depth, floor space per person, precautionary measures, building value, and building quality. The high importance of water depth is in accordance with traditional stage-damage functions. However, to the best of our knowledge, the influences of other parameters have not been studied comprehensively for flood damage assessment in Australia.

Finally, the performance of the tree-based models was compared with the outcomes of a newly established multi-parameter flood loss function (FLFA_{rs}) from Australia. It is demonstrated that the new tree-based model, due to considering more parameters, can estimate the extent of losses more accurately. The evaluation of model performance in this chapter is based on random samples which are not independent of the data used for model development. Hence, the comparison of model performance does not give information about the transferability of the models.

Accordingly, it is recommended that further development of Australian flood damage models consider more candidate predictors (especially the important parameters stated in this study), and take advantage of tree-based models. Further research will be aimed at examining a more comprehensive dataset to explore the significance of other influencing factors (e.g. return period, long duration flooding, sediment loading, and early warning) and using an independent dataset to evaluate the level of transferability of the tree-based models in time and space.

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7 PREDICTIVE APPLICATIONS OF AUSTRALIAN FLOOD LOSS MODELS AFTER A TEMPORAL AND SPATIAL TRANSFER [Submitted Chapter] ⁵

7.1 Abstract

In recent decades, considerably greater flood losses have increased attention to flood risk evaluation. This study used datasets collected from Queensland flood events and investigated the predictive capacity of three new Australian flood loss models to assess the extent of physical damages, after a temporal and spatial transfer. The models' predictive power is tested for precision, variation, and reliability. The performance of a new Australian flood loss function (FLFARs) was contrasted with two tree-based damage models, one pruned and one un-pruned. The tree-based models are grown based on the interaction of flood loss ratio with 13 examined predictors gathered from flood

⁵ Hasanzadeh Nafari, R. and Ngo, T., 2018. Predictive applications of Australian flood loss models after a temporal and spatial transfer, *Geomatics, Natural Hazards and Risk*, 9:1, 416-430.

specifications, building characteristics, and mitigation actions. Besides an overall comparison, the prediction capacity is also checked for some sub-classes of water depth and some groups of building type.

It has been shown that considering more details of the flood damage process can improve the predictive capacity of damage prediction models. In this regard, complexity with parameters with low predictive power may lead to more uncertain results. On the other hand, it has also been demonstrated that the probability analysis approach can make damage models more reliable when they are subjected to use in different flooding events.

7.2 Introduction

Flood is a common natural disaster in Australia, and a frequently occurring natural phenomenon in the world (Baeck et al., 2014; Bhatt et al., 2016; Hasanzadeh Nafari et al., 2015). In recent decades, flood impacts have increased (Cheng and Thompson, 2016; Kreibich et al., 2007; McMillan et al., 2016; Mojaddadi et al., 2017), reaching 29% of the total cost of Australian natural disasters (Bureau of Transport Economics, 2001). Hence, flood risk evaluation including hazard assessment and estimation of the associated consequences (Ciullo et al., 2016; Vojtek and Vojteková, 2016) has attracted growing attention (Cammerer et al., 2013; Kundzewicz et al., 2013; Merz et al., 2010; Raaijmakers et al., 2008). While much effort has gone into hazard investigation, i.e. models of probability and intensity of flood, flood loss estimation models are still subject to a high level of uncertainty (Kreibich and Thieken, 2008; Merz et al., 2004; Meyer et al., 2013). Loss estimation is needed in cost-benefit analyses of disaster risk reduction measures (Mechler, 2016), vulnerability and resilience studies, flood risk analyses, and in the insurance and reinsurance sectors (de Moel and Aerts, 2011; Schröter et al., 2014).

Flood impact can be classified as direct or indirect damage (Molinari et al., 2014; Thieken et al., 2005). Direct losses happen in the flood boundary and due to the physical impacts of water on flooded objects (e.g. humans, properties, building contents

or any other objects), while indirect flood damages could occur outside the flooded area or after inundation time (Chen et al., 2016; Novelo-Casanova and Rodríguez-Vangort, 2016). Both direct and indirect losses can be categorised as tangible or intangible consequences (Gissing and Blong, 2004; Thieken et al., 2005). Tangible losses can be estimated in fiscal terms, but intangible losses are non-marketable (Chinh et al., 2015). The focus of this study is to physical, tangible impacts of flood and the spatial scale is on the order of individual residential buildings.

Although there is currently no widely accepted method for estimating flood damage in urban areas, most approaches rely on stage-damage functions for simplicity (Luino et al., 2009; Merz et al., 2010; Meyer et al., 2013). Stage-damage functions, which date back to White (1945) (White, 1945) are usually based on the level of the water and vulnerability of the buildings at risk (Schröter et al., 2014; Thywissen, 2006). The functions establish a relation between the level of water (i.e. flood magnitude) and the expected damages for specific building vulnerability classes (Dewals et al., 2008; Jongman et al., 2012; Thieken et al., 2006). Nonetheless, there are some exceptions which account for further impact parameters such as flow velocity, water contamination, duration of inundation, individual precautionary behaviour, or early warning time (Cammerer et al., 2013; Hasanzadeh Nafari et al., 2016c; Merz et al., 2013). Stage-damage functions can be derived based on real damage data (i.e. empirical curves), or they can be developed by “what-if” questions (i.e. synthetic curves) (Amadio et al., 2016; Smith, 1994). Each approach has some advantages and disadvantages (Merz et al., 2010). Flood loss functions can also be grouped as absolute or relative. The absolute type expresses the extent of losses in fiscal terms, while relative functions show the magnitude of damages as a ratio of the asset price, i.e. replacement or depreciated cost of the property, and are independent of market variations (Kreibich et al., 2010).

On the other hand, flood damage might be controlled by a variety of influencing parameters rather than the ones considered in stage-damage functions (Schröter et al., 2014). Merz et al. (2013) have classified these parameters into flood intensity factors

including depth of water, flow velocity, return period, duration, and contamination of water; and building flood-resistant indicators including material and characteristics of property, individual precaution and emergency actions, early warning time and preparedness, former flood experience of residents, and residents' socioeconomic situations (Merz et al., 2013). Accordingly, data mining techniques, as effective alternatives to traditional stage-damage functions, have recently been used for exploring the interaction and the importance of different damage-influencing parameters in Germany, the Mekong Delta, and Australia (Chinh et al., 2015; Hasanzadeh Nafari et al., 2016c; Kreibich et al., 2016; Merz et al., 2013). These studies are showing that the impacts of different affecting factors can be studied effectively with the tree-based data mining technique, which is mostly utilised in water resource studies and hydrology science, but rarely in flood-loss modelling (Merz et al., 2013).

Flood loss models (whether stage-damage functions or tree-based models) are sharply restricted to the features of the area of origin (i.e. flood features and building characteristics) (Hasanzadeh Nafari et al., 2016a). Thus, transferring the damage models to a new study area and/or a new flood event does not result in an accurate relationship between the extent of damages and the impacts of flood, unless the models have been calibrated with an empirical dataset collected from the new case study (Cammerer et al., 2013; Luino et al., 2009; Oliveri and Santoro, 2000). This loss of accuracy naturally reduces predictive capacity (Schröter et al., 2014). On the other hand, the largest effect on loss estimation is induced by the shape of the applied damage models, while precision in collecting hydraulic input and flood characteristics is of minor importance (Apel et al., 2009; de Moel and Aerts, 2011). Therefore, validation of flood loss models is one important step in model development (Cammerer et al., 2013; Schröter et al., 2014). However, due to a lack of historical data, little research has been done on the validation of models, especially when they are subjected to a temporal and/or spatial transfer (Merz et al., 2010; Meyer et al., 2013; Seifert et al., 2010; Thielen et al., 2008), and Australia is no exception.

This study, therefore, attempts to explore the predictive performance of three newly derived Australian flood loss models, one stage-damage function and two tree-based models, after a temporal and spatial transfer. Firstly, all three models are developed and calibrated based on the empirical dataset collected from one flood event that occurred in Queensland at the beginning of 2013. Afterwards, their predictive capacity is compared and contrasted with the official damage data of the 2012 flood event. The models' predictive power is tested regarding precision, variation, and reliability of the results. The prediction capacity is also checked for some sub-classes of water depth and some groups of building type.

7.3 Flood Events and Damage Data

7.3.1 Study Area and Flood Event in 2013

The study area of the 2013 flood event is the city of Bundaberg, on the Burnett River in south-east Queensland. Due to its geographical characteristics (e.g. location and ground elevation), shown in Figure 7-1, this city has seen several flood disasters in recent years. One of the most significant happened in January 2013 (Hasanzadeh Nafari et al., 2016b). The flood happened after Tropical Cyclone Oswald and its associated rainfall (Alamdard et al., 2016). The flood had significant negative consequences on Bundaberg's economy as more than 2000 buildings were impacted, and damage to public infrastructure was estimated around AUD103 million (Hasanzadeh Nafari et al., 2016a). The maximum level of flood water was recorded as 9.53 metres and its return period was estimated as 100 years (North Burnett Regional Council, 2014). An empirical dataset including information on the hazard intensity, the vulnerability of buildings and the associated damages used for the models' development was collected after this flood event.

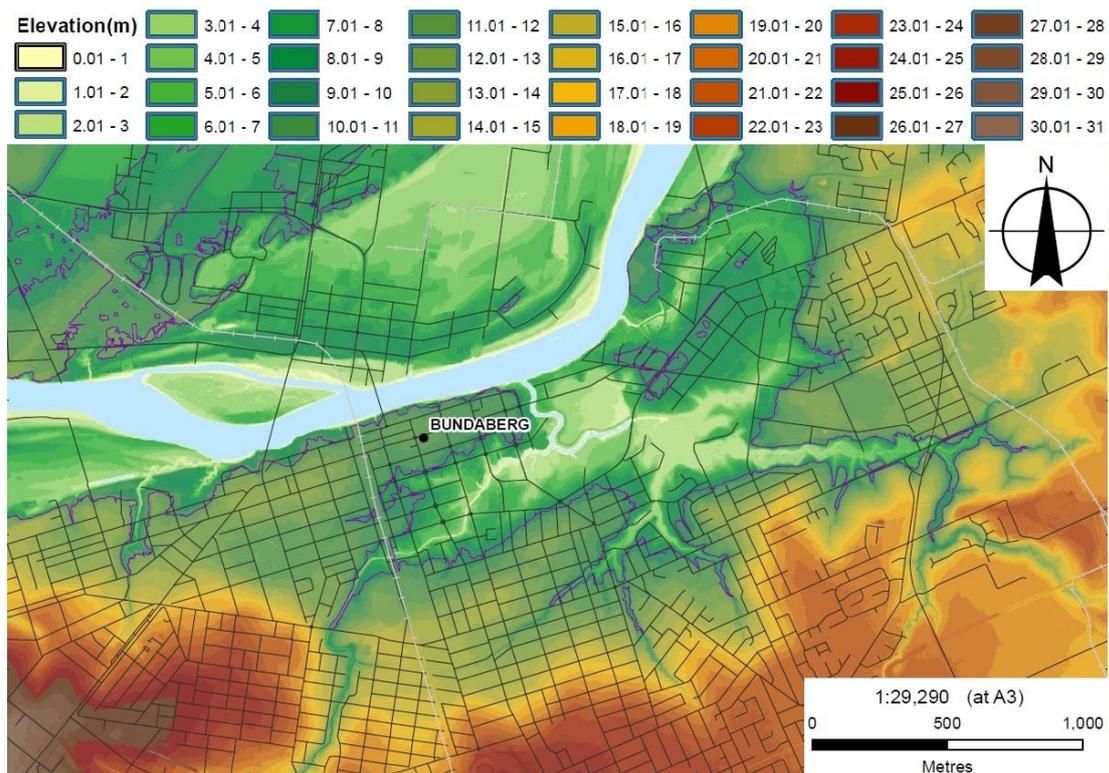


Figure 7-1: Topographic map of Bundaberg (Bundaberg Regional Council, 2013)

7.3.2 Study Area and Flood Event in 2012

The second area of study is the city of Roma, and the dataset used for the cross-regional and temporal model validation was collected from a flood event that occurred there in February 2012. The city of Roma is in the Maranoa region in Queensland, on the Condamine River. The flood event, which happened due to an intense rainfall, damaged more than 444 residential properties. It was a rare disaster in Roma’s 149-year history and its return period was estimated as 100 years (North Burnett Regional Council, 2014). The inundation boundary is shown in Figure 7-2.

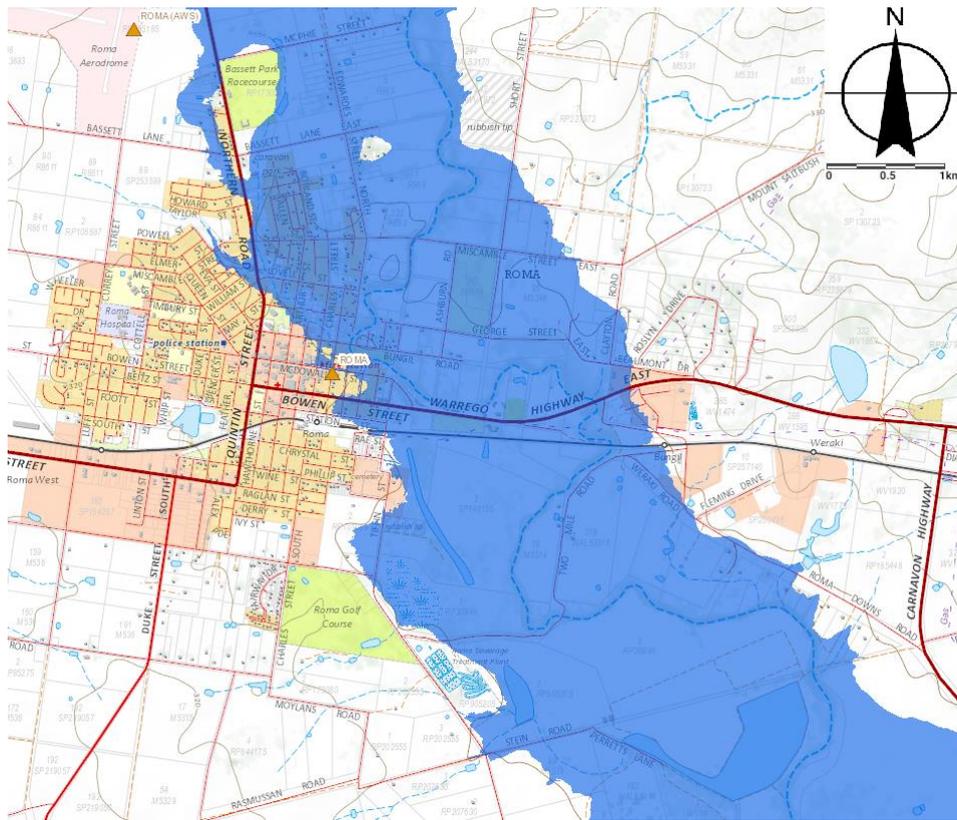


Figure 7-2: Flood inundation boundary in the area of the study after the 2012 inundation event (Qld Department of Natural Resources and Mines, 2015)

7.3.3 Empirical Damage Data Collection

Queensland Reconstruction, as a government authority for responding to Queensland natural disasters, has collected and provided the dataset used in this research including 250 data samples from the 2012 flood and 607 samples from the 2013 flood. The official dataset, which was compiled from post-disaster on-site surveys, includes information on flood impacts (e.g. depth, velocity, contamination), specifications of the affected buildings (type of building and number of storeys, construction material, area of the building, protection of mechanical and electrical utilities, and emergency measures undertaken), and the extent of losses. The empirical dataset expresses the magnitude of losses by illustrating the status of all structural components in post-disaster time (i.e. which components are undamaged and which ones are partially or

entirely damaged). Accordingly, the damage ratio was calculated by dividing the replacement cost of the affected components by the total replacement cost of the property (Hasanzadeh Nafari et al., 2016a). More data about the affected buildings (e.g. age and total replacement value) and the status of their residents was gathered from the NEXIS (the National Exposure Information System of Australia) database (Dunford et al., 2014).

7.4 Damage Models

In this study, the performance of three newly established Australian models, different in approach and complexity, was compared and contrasted with real system data. All models were calibrated and developed based on the same dataset gathered from the 2013 flood event in Queensland. After a spatial and temporal transfer, their predictive capacity was assessed in comparison to the 2012 damage data.

7.4.1 FLFA_{rs}

The Flood Loss Function for Australian residential structures (FLFA_{rs}) is newly developed by Hasanzadeh Nafari et al. (2016b) (Hasanzadeh Nafari et al., 2016b). The FLFA_{rs} is an empirical-synthetic model, meaning that this model was initially developed using a simplified synthetic approach called the sub-assembly method, developed by the HAZUS manual (FEMA, 2012). Then, the synthetic curves were calibrated using the data of the 2013 flood event in Queensland. To be more precise, this model takes the empirical data of damage and depth, stratified by building classifications, and uses the chi-square test of goodness of fit to fit a parameterised function to compute depth-damage estimates.

The chapter has illustrated a bootstrapping approach to assist in exploring the inherent uncertainty of the empirical data and the associated confidence limits around parameters of the stage-damage function. For every building (i.e. one- and two-storey buildings with masonry and timber walls) three stage-damage functions (i.e. most likely, maximum, and minimum damage functions) are depicted. In more detail, for each type of building, using a bootstrapping approach and the chi-square test,

resampling of the related empirical loss values was carried out for 1,000 times, and 1,000 sets of functional parameters were generated. Afterwards, the average of the 1,000 sets of functional parameters was converged to the values considered for the most likely curve which produces the smallest error. The function that maximises the depth damage relationship was taken as a maximum curve, and the observation that created the minimum depth damage relationship was taken as the minimum curve (see Figs. 7-3, and 7-4). As mentioned, the range of estimates represents the epistemic uncertainty of the empirical dataset (Hasanzadeh Nafari et al., 2016b).

The advantages of this approach compared to most Australian synthetic models include the ability to utilise empirical data; considering the epistemic uncertainty about the depth damage relationship and representing robust damage curves; and capacity to easily change functional parameters based on different characteristics of Australian buildings. The stage-damage functions utilised in this study for one-storey buildings with timber walls and two-storey buildings with brick walls are the most likely curves shown in Figs. 7-3 and 7-4.

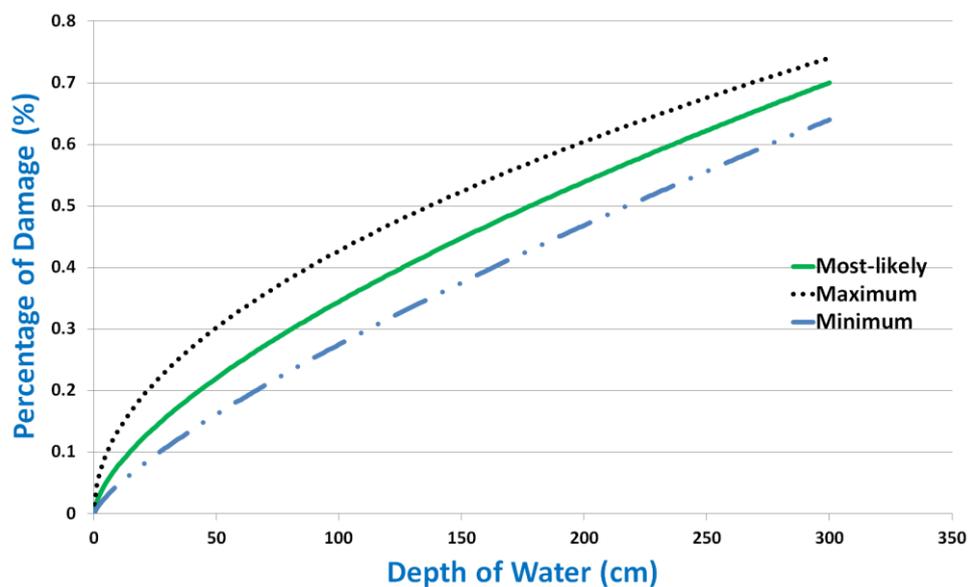


Figure 7-3: Minimum, most likely and maximum FLFARs stage-damage functions for one-storey buildings with timber walls (Hasanzadeh Nafari et al., 2016b)

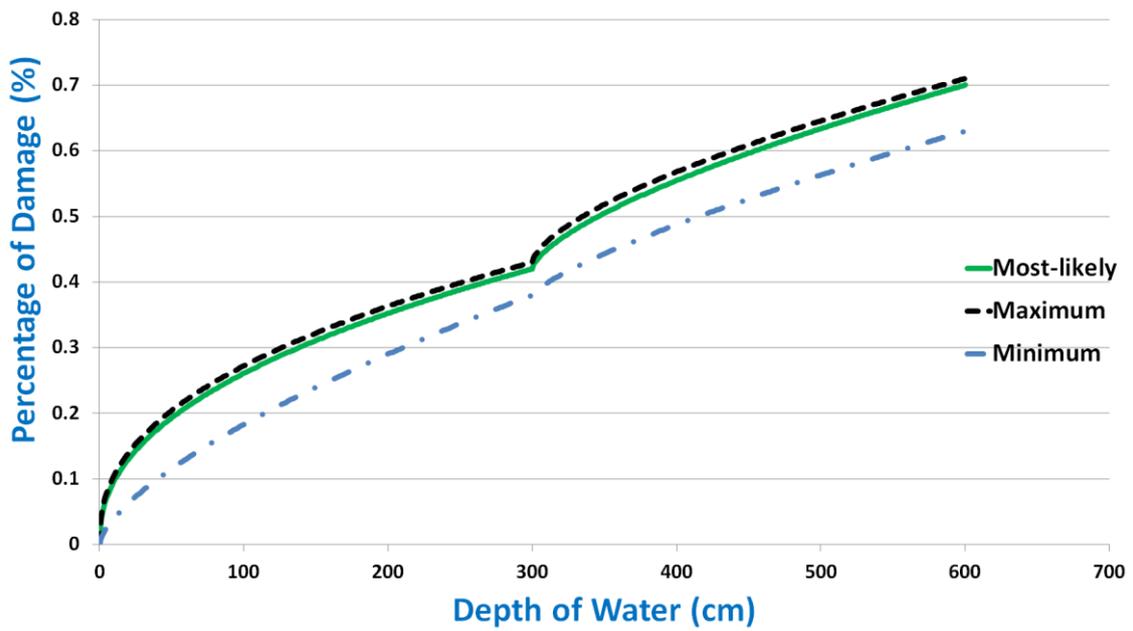


Figure 7-4: Minimum, most likely and maximum FLFARs stage-damage functions for two-storey buildings with timber walls (Hasanzadeh Nafari et al., 2016b)

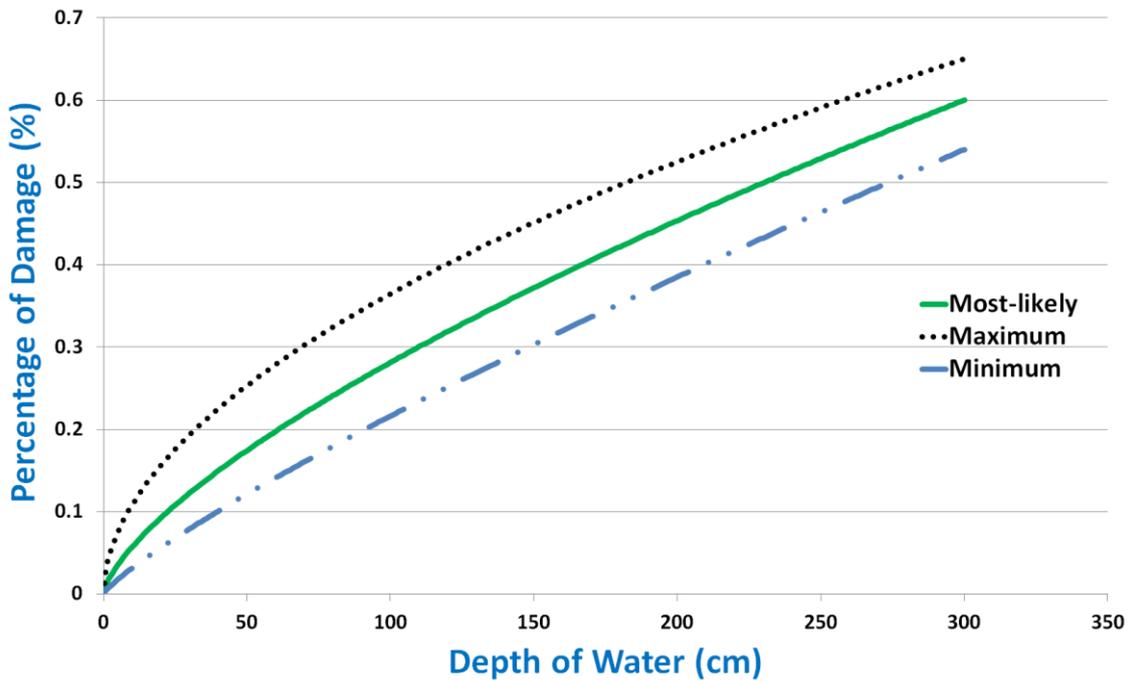


Figure 7-5: Minimum, most likely and maximum FLFARs stage-damage functions for one-storey buildings with brick walls (Hasanzadeh Nafari et al., 2016b)

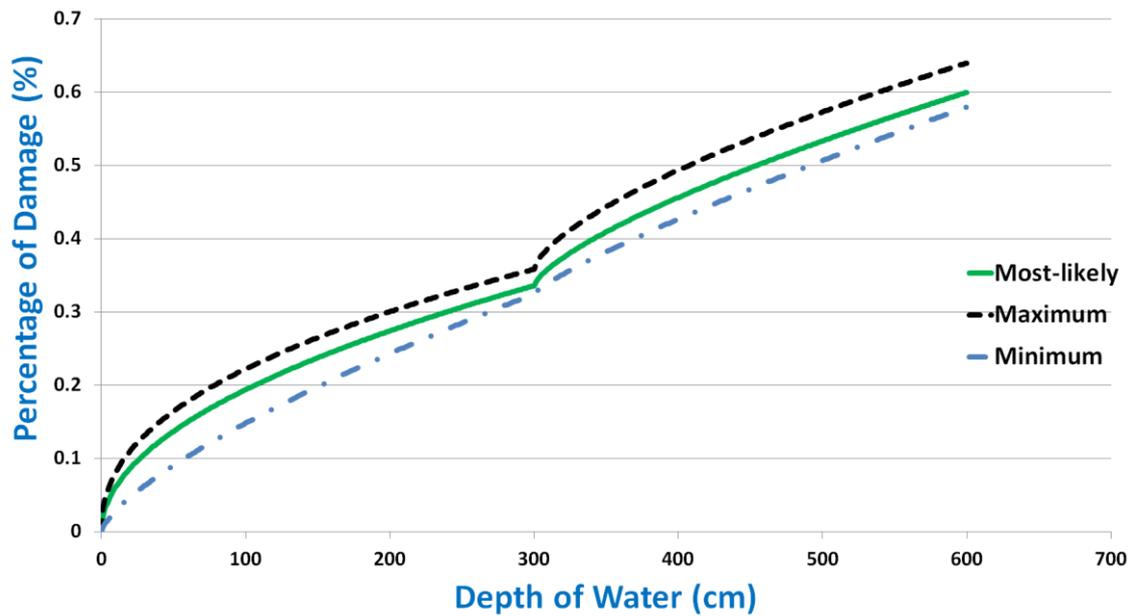


Figure 7-6: Minimum, most likely and maximum FLFARs stage-damage functions for two-storey buildings with brick walls (Hasanzadeh Nafari et al., 2016b)

7.4.2 Regression Trees

Regression trees were drawn based on the approach of Hasanzadeh Nafari et al. (2016c). Compared to the outcomes of that study, the model has been redeveloped, and its shape has been adapted based on the data from the 2013 flooding event. Data preparation and ranking of the examined predictors are described in Hasanzadeh Nafari et al. (2016c) (Hasanzadeh Nafari et al., 2016c). The 13 candidate predictors considered for data mining are classified and represented in Table 7-1.

Table 7-1: Explanation of the examined predictors considered for data mining (Character of Variables: Co: continuous, No: nominal, Or: ordinal) (Hasanzadeh Nafari et al., 2016c)

Divisions	Examined Predictors		Variables Character	Variation
Hazard intensity	WD	Depth	Co	between 0 cm and 680 cm above ground elevation
	Vel.	Velocity	Or	1 = calm to 3 = high
	Con.	Contamination	Or	0 = no contamination to 2 = massive contamination
Emergency measures	EM	Emergency actions	Or	0 = no action to 3 = many actions
Precaution, experience	PM	Precaution actions	Or	1 = no action undertaken to 4 = many actions undertaken
	Exp.	Former flood experience	Or	1 = few experience to 3 = many experience
Building specifications	BQ	Quality of property	Or	1 = very poor to 6 = well-behaved
	BV	Value of property	Co	1756 to 3594000 AUD
	FS	Floor space per person	Co	13 to 870 m ²
Residents socioeconomic situation	RA	Residents need assistance	No	0 = don't need, 1 = need
	Own.	Ownership status	No	0 = renter, 1 = owner
	Inc.	Monthly income	Or	1 = \$1-\$600, 2 = \$601-\$2000, 3 = more than \$2000
	LE	Low education residents	No	0 = No, 1 = Yes

Data mining was carried out using tree-based analysis and Weka machine learning software algorithms (Kalmegh, 2015). Branches were generated in a way which maximises the predictive capacity of the model, and prediction of damage ratio in every terminal node was carried out based on the average value of all loss ratios dedicated to the node (Kreibich et al., 2016). In the tree-based analysis, the overfitting issue needs careful attention (Merz et al., 2013). This issue can affect the prediction capability of a model if it is fully developed on one dataset (Breiman et al., 1984; Pal and Mather, 2003). Then, trees should not be made complicated by branches which do not enhance

the prediction capability of models. Tree pruning is one way to avoid this issue. This technique works by eliminating the parts of the tree that do not improve the accuracy of results (Bramer, 2007). In other hand, trees should not be too simple, and they should take advantage of branches that could enhance the predictive capability of the model (Merz et al., 2013).

Accordingly, in this study, to choose the most accurate model with a better predictive capacity taking into account the spatial and temporal transfer, two trees (i.e. one pruned, with 12 terminal nodes, and one un-pruned, with 21 terminal nodes) were grown and utilised (see Figs. 7-5 and 7-6). These sizes were selected due to the minimum value of the error (MAE) calculated by a 10-fold cross-validation test on the original dataset (i.e. the 2013 flood event data). For the error calculation, the damage records were randomly partitioned into ten subsets. Then, ten iterations of model calibration and model testing were carried out. In each iteration, the model was calibrated using nine subsets of the data, while the picked-out subset was kept for the model testing. In the end, errors were calculated by averaging over all ten iterations (Refaeilzadeh et al., 2009).

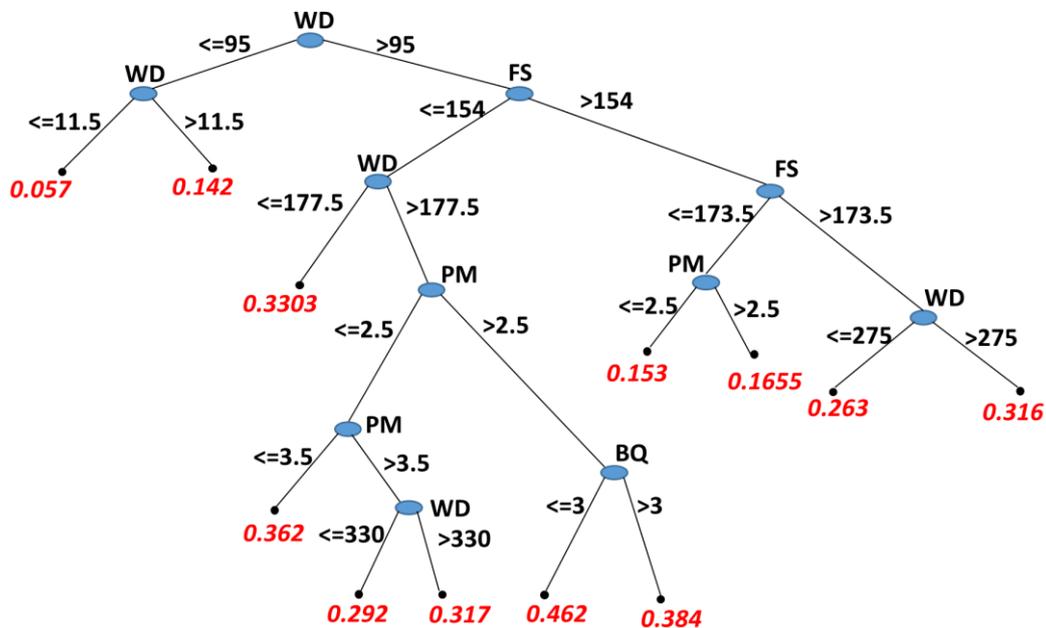


Figure 7-7: Pruned tree (RTp) with 12 leaves (for the description of the examined predictors, see Table 7-1)

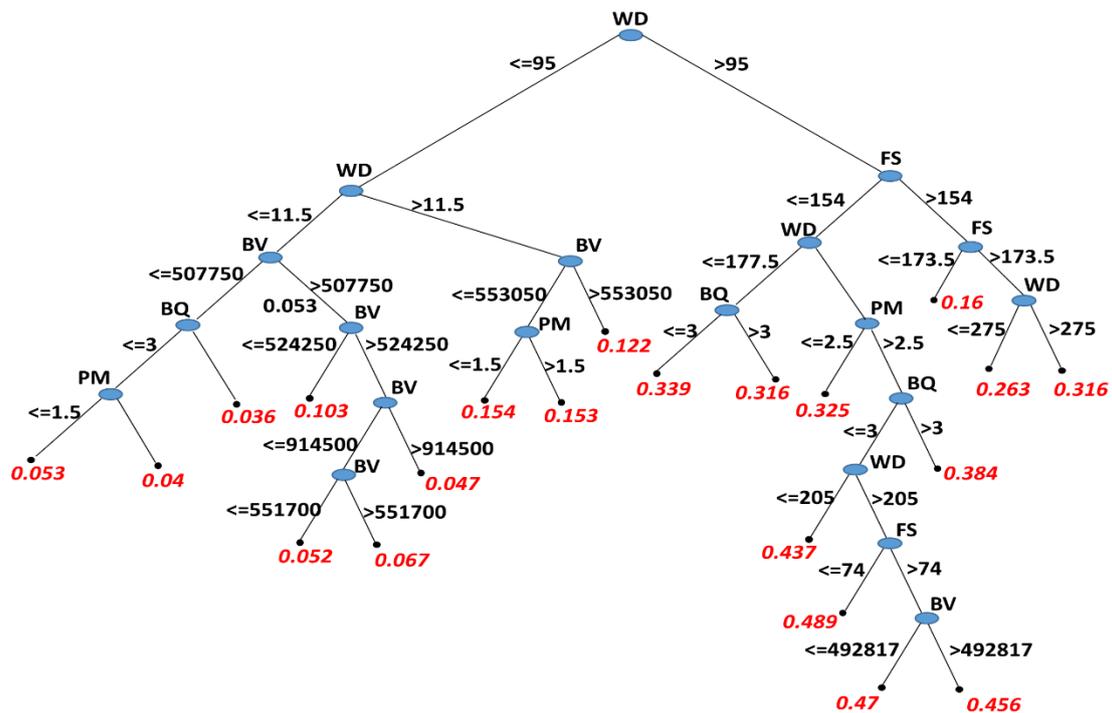


Figure 7-8: Unpruned tree (RTup) with 21 leaves (for the description of the examined predictors, see Table 7-1)

As shown in Fig. 7-5, flood depth, precaution actions, floor space, and quality of property by having, respectively, five, three, two, and one decision nodes are the influencing variables of the pruned regression tree. Also, Fig. 7-6 represents the importance of building value, water depth, floor area, quality of property and precaution actions in the unpruned model by taking six, five, three, three, and three decision nodes, respectively. As is evident, the advantage of the tree-based model can be addressed to the ability to consider more damage-influencing parameters, while it does not reflect the inherent uncertainty of the dataset.

7.5 Validation of the models

As stated earlier, model validation is a major step in model development, but due to a lack of historical data, has been widely neglected. Model validation should represent the intended purpose of the model and may represent the replicative application or the predictive application of a damage model. The replicative validation approach, which

was used by Hasanzadeh Nafari et al. (2016c) (Hasanzadeh Nafari et al., 2016c), refers to the performance of the model on a dataset which has been used in model development. The predictive validation process assesses the model's capability of predicting an independent dataset (Power, 1993; Schröter et al., 2014). The focus of this work is on the predictive validation approach after a spatial and temporal transfer, and the authors have attempted to explore the suitability of the models as compared to real system data.

To test the predictive capability of the models, 200 sets of 250 affected buildings were randomly drawn from the original dataset; each model was applied to every building record and results were calculated and averaged over all samples. Following the approach of Schröter et al. (Schröter et al., 2014), the models' predictive capacity was tested for the precision of the outcomes, variation of the residuals, and reliability of the results. Accordingly, precision was tested by MBE and MAE. The MBE as the overall bias error is negative if predicted damage values are smaller than actual loss records, and it is positive if an overestimation has occurred in prediction. Also, MAE represents that how much predictions are adjacent to real damage data (Chai and Draxler, 2014). Residuals variation has been checked by the Coefficient of Variation (CV) measurement, which represents the extent of variability in relation to the mean of the population. A smaller CV shows a lower spread of prediction errors (Hasanzadeh Nafari et al., 2015). The models' reliability has been examined using the Hit Rate (HR) value, which illustrates the percentage of damage records that included in the 90 percent range (i.e. 95-5 quantiles interval) of predicted values (Schröter et al., 2014). This quantile interval represents the nominal coverage rate of 90 percent of model outcomes. Accordingly, the model performance shows a perfect reliability if the HR is equal to 0.9, i.e. the nominal coverage rate of 90 percent of model outcomes is equal to the coverage rate of actual damage records (Schröter et al., 2014; Thordarson et al., 2012). The models' evaluation criteria are calculated as follows:

Table 7-2: Model evaluation criteria (e_i is deviation of the estimated values from real damage data; σ and μ are the standard deviation and the mean value of the model residuals)

Criterion	Formula	LB ¹	UB ¹	PP ¹
MAE	$\frac{1}{n} \sum_{i=1}^n e_i $	0	+inf	0
MBE	$\frac{1}{n} \sum_{i=1}^n e_i$	-inf	+inf	0
CV	$\frac{\sigma}{\mu}$	0	+inf	0
HR	$\frac{1}{n} \sum_{i=1}^n h_i; h_i = \begin{cases} 1, & \text{if } O_i \in [Q_{95i}, Q_{05i}] \\ 0, & \text{otherwise} \end{cases}$	0	1	0.9

¹LB: Lower Bound, UB: Upper Bound, PP: Perfect Prediction

7.6 Results and Discussion

The accuracy of the results and the validation of the models' performance was tested three times. Firstly, the overall performance of the aforementioned models, calibrated with the 2013 data, was tested for predicting the extent of losses of the 2012 flood event. Afterwards, the water depth “d” was divided into six different groups (d<20 cm, 20<d<40 cm, 41<d<60 cm, 61<d<80 cm, 81<d<100 cm, d>101 cm), and the models' outcomes were contrasted with the corresponding damage data. Finally, the buildings were grouped into four classes (one-storey timber buildings, two-storey timber buildings, one-storey masonry buildings, and two-storey masonry buildings) and the evaluation was repeated. Table 7-3 represents the results of the overall comparison, which are calculated by averaging over all sample outcomes.

Table 7-3: Comparison of the models' predictive capacity for the flood event of February 2012 (RT_p is the pruned regression tree, and RT_{up} is the un-pruned regression tree)

Methods	MAE	MBE	CV	HR
FLFA _{rs}	0.06	- 0.02	1.08	0.79
RT _p	0.04	- 0.01	0.78	0.53
RT _{up}	0.09	- 0.03	0.75	0.43

Overall, all three models, newly derived for Australian geographical conditions, perform well (due to a slight underestimation; low variation and acceptable reliability in results). However, as to precision, Table 7-3 shows that the pruned tree, compared to FLFA_{rs}, is better for predicting the 2012 flood event, having fewer values of mean bias error. This accuracy is due to considering more influencing parameters and having more complexity, which increases the capability to predict flood damage, especially when the model is transferred in time and space. Also, the un-pruned tree that was grown fully on the original data is less precise on an independent dataset. The result confirms the hypothesis of the lower prediction ability of an un-pruned tree on an independent system data (i.e. a low generalisation capability), signifying a low level of transferability in time and space (higher rigidity to the original system data). The RT_{up} might also be subject to an additional source of uncertainty since additional variables are taken into account. It is worth noting that all damage models, on average, show a slight negative bias from the actual damage values which indicates an approximate 1 to 3 percent underestimation in predictions. The variation of the errors was checked based on the distributions of the residuals (CV), and FLFA_{rs} shows more variation in the results.

As stated earlier, the HR indicator, i.e. the percentage of damage records included in the 90 percent interval of predicted values, which was utilised for testing and comparing the reliability of the models' predictions. According to Table 7-3, the performance of

FLFA_{rs} is more reliable, since the HR indicator is 0.79 (very close to 0.9 as the nominal coverage rate of 90 percent of model outcomes). This matter accords with the variation test outcomes. Consequently, the reliability of the models seems to be more dependent on the model approach. The FLFA_{rs}, as opposed to the other deterministic models (e.g. RT_p and RT_{up}), is a probabilistic dependence model that depicts the most likely relationship among the water depth, the building characteristics and the percentage of damages (Hasanzadeh Nafari et al., 2016b; Lehman and Hasanzadeh Nafari, 2016). The reliance of this approach on the probability distributions of damage ratios has increased its performance reliability.

As mentioned before, the predictive capability has also been studied for some sub-classes of water depth and building characteristics. Figs.7-7 and 7-8 show the precision (the Euclidean Distance of the MAE and MBE errors) of the results for six different sub-classes of water depth and four groups of building types.

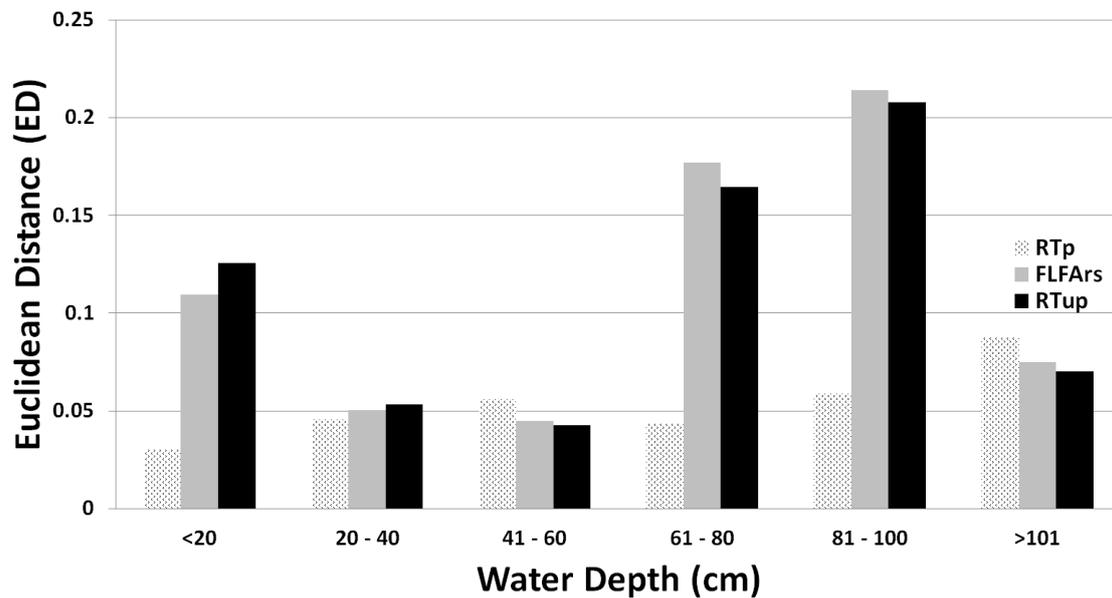


Figure 7-9: Comparison of the models' precision per water-depth class

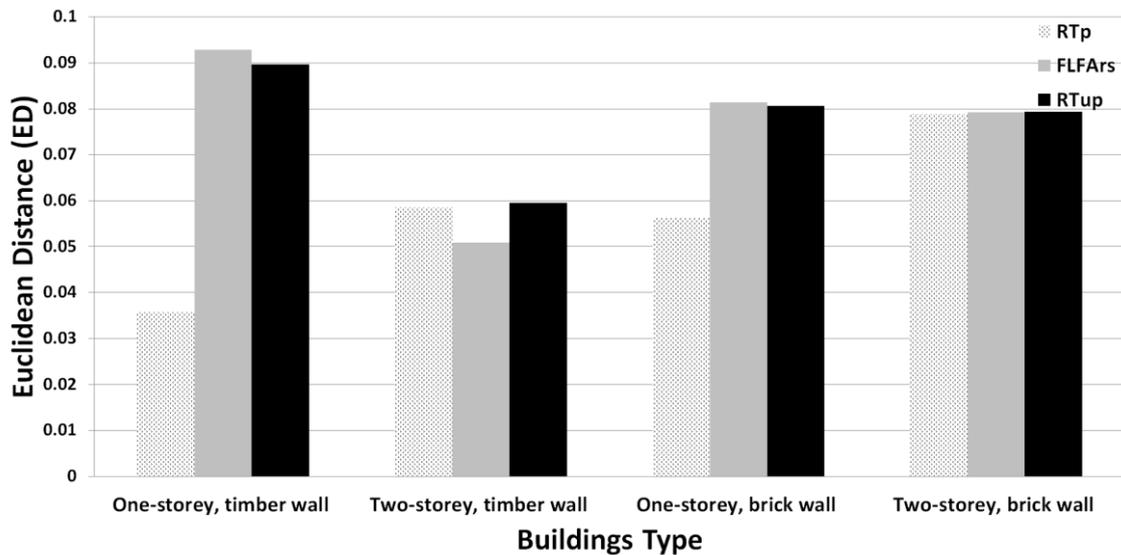


Figure 7-10: Comparison of the models’ precision per building type

Fig. 7-7 shows that the uncertainty of the pruned tree is less than the other two models, except when the water depth is between 41 and 60 centimetres or is more than 101 centimetres. In these two cases, FLFA_{rs} and RT_{up} approaches show a slightly better performance. Fig. 7-8 also depicts less uncertainty and more accuracy in the results for the transferred pruned tree in contrast to the other two flood damage models. However, FLFA_{rs} performs better for the two-storey timber buildings.

The above differences in the magnitude of the errors related to the critical sub-classes for RT_p damage predictions are not too considerable, and the results justify the overall better performance of the pruned tree, after transferring and using in a new area of study. This matter accords with the earlier findings. However, the outcomes would indicate the use of FLFA_{rs} if the critical water depth coincides with the critical type of the building (i.e. the water depth is between 41 and 60 centimetres or is more than 101 centimetres, and the structure is a two-storey building with timber walls).

7.7 Conclusions

Flood is a frequently occurring natural disaster with significant adverse consequences for Australian societies. Hence, flood risk management and flood risk reduction are attracting growing attention. In this context, damage assessment and loss prediction is an important component of flood risk mitigation. Although there is no widely accepted method of flood loss assessment, traditional stage-damage functions, due to simplicity, are accepted as the international standard for estimation of direct losses. These functions estimate the extent of losses by establishing a relationship among water depth, type of building at risk, and magnitude of damages. On the other side, flood as a complicated process may be controlled by more influencing parameters which are neglected in the traditional stage-damage functions. In this regard, tree-based analysis and data mining have recently been used to create some new flood loss estimation models with more complexity and more damage-influencing parameters.

Although a variety of approaches are used in today's studies, flood damage assessment models are still subject to a high level of uncertainty. Model validation, which is dependent on flood features and building specifications, has the largest effect on the accuracy of results. Model validation needs more careful attention if the damage model is used in a new study area and/or applied to a new flood event. However, due to a lack of historical data, model validation has been widely neglected in Australia. This study, therefore, has attempted to explore the validation and the predictive performance of three newly established flood loss models from Australia, different in approach and complexity (i.e. one stage-damage function and two tree-based models), after a temporal and spatial transfer. All three models were developed and calibrated with the data from the 2013 Queensland flood event. Their predictive capacity was compared and contrasted with the official loss records of the 2012 flood event. The models' predictive power was tested for precision, variation, and reliability.

The flood stage-damage function utilised in this study (FLFA_{rs}) is an empirical-synthetic model that relies on the probability distributions of damage ratios. This newly derived model is a probabilistic dependence model that depicts the most robust

relationship among the water depth, the building characteristics, and the percentage of damages. This stage-damage function has been developed by considering the epistemic uncertainty about the depth damage relationship. In addition to the stage-damage function, two tree-based models have also been grown in this study. The trees are similar in approach and different in complexity, one being a pruned tree with less complexity, and the other an un-pruned fully grown tree with more complexity. These models are grown on the basis of the minimum value of the errors, and the importances and influences of 13 candidate predictors (i.e. depth of water, velocity, contamination of flood, private precautionary actions, emergency actions undertaken, former flood experience, area of building per person, average value of property, quality and resistance of property, and residents' socioeconomic situation).

Results show that the pruned tree is better for predicting the 2012 flood event, having less uncertainty of results. This accuracy is due to the complexity of the model (i.e. considering more damage-influencing parameters) which increases the capability to predict flood damages, especially when the model is transferred in time and space. Results also confirm the low level of transferability of the fully grown un-pruned tree, which is due to the low generalisation capability of this model. In addition, it has been shown that the performance of FLFA_{rs} is more reliable than the other two models. Accordingly, the reliability of the models seems to be more dependent on the model's approach rather than its complexity. As stated above, FLFA_{rs}, as opposed to the tree-based deterministic models, is a probabilistic dependence model. The reliance of this approach on the probability distributions of damage ratios has increased the reliability of its performance. Besides this overall comparison, this study has also explored the accuracy of the results and compared the performance of the models for some subclasses of water depth and building type. Generally, the results accord with the overall comparison outcomes. However, this detailed analysis indicates the use of FLFA_{rs} for floods with a depth ranging from 41 centimetres to 60 centimetres or more than 101 centimetres and buildings with a two-storey structure and timber walls.

All in all, considering more details of the damaging process can be useful for improving the predictive capacity of Australian flood damage prediction models and enhancing the level of transferability. In this regard, statistical tests need careful attention, since complexity with parameters with low predictive power might have adverse effects on the outcomes and may increase the level of uncertainty of the results. Furthermore, reliance on probability analysis can intensify the reliability of damage models when they are subjected to use in different flooding events of Australia.

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Chapter 7: Predictive Applications of Australian Flood Loss Models

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8 CONCLUSIONS

8.1 Overview

This research developed a validated flood damage assessment framework for the geographical area of Australia using historical data collected from recent extreme events. The results will provide decision-makers with an essential tool for planning better risk mitigation strategies and actively responding to flood disasters.

Firstly, a comprehensive data set including information on the extent of damage, flood impact variables, and resistance factors was collected from the 2012 and 2013 flood events in Queensland, Australia. Then, data mining, data preparation and data transformation were conducted. Afterwards, based on the sub-assembly approach and the variability in the vulnerability and value of structural components, a novel empirical-synthetic method was suggested. The new method was a general methodology for quickly estimating the extent of losses for each stage of water, and suggested simple and flexible curves with regards to the changeability in building practices.

Since the function approach is a common and internationally accepted methodology for estimating the value of flood losses, some new relative multi-parameter flood damage assessment functions were derived, calibrated, and validated for the most common residential and commercial building types in Australia. The functions were developed using the bootstrapping approach and considered the inherent uncertainty in

Chapter 8: Conclusions

the data sample, the variability of real-world circumstances, and the probabilistic relationship between vulnerability features of the properties and depth of water. Finally, the performance of the new models, in comparison to the empirical data, was contrasted with well-known flood damage assessment models from Australia and overseas.

The constructed modelling approach was then transferred to a study area in Italy to check the ease of using local empirical data, evaluate the accuracy of the outcome and assess the ability to change parameters based on building practices across the world. In this study, the new model was calibrated using empirical damage data collected from a recent flood event in the region of Emilia-Romagna, and the performance of the model was validated for the prediction of loss ratios and absolute damage values. Furthermore, the predictive capacity of the model was studied for some sub-classes of water depth, and it was contrasted with other damage models frequently used in Europe.

As flood damage assessment is a complicated process and might be dependent on a variety of parameters which are neglected in stage-damage functions, tree-based models (regression trees and bagging decision trees) were developed for exploring the interaction, importance, and influence of different damage-influencing parameters on the extent of losses (e.g. depth of water, flow velocity, contamination of water, material and characteristics of property, individual precautions and emergency actions, former flood experience of residents, and residents' socioeconomic situations). This tree-based data mining approach, a new approach in flood-loss modelling, has tried to analyse the whole gamut of influencing factors, and assess their single or joint effects more comprehensively. In addition, the newly derived tree-based model was used for predicting the magnitude of damage and its performance was validated and compared with the outcomes of a stage-damage function.

In the last part of this research, the authors have explored the predictive performance of the new approaches (i.e. flood loss functions and tree-based flood loss models) in

assessing the extent of physical damages after a temporal and spatial transfer. The performance of the newly derived flood loss function was contrasted with two tree-based damage models, one pruned and one un-pruned. The tree-based models were created based on the interaction of flood loss ratio with 13 examined predictors gathered from flood specifications, building characteristics and mitigation actions. The predictive power of the models was tested in terms of precision, variation and reliability. The prediction capacity was also checked for some sub-classes of water depth and some groups of building type.

8.2 Conclusions

The main findings and outcomes of this research can be summarised as follows:

- The first advantage of the newly derived stage-damage functions is related to the capacity to utilise empirical data. Due to calibration of $FLFA_{rs}$ and $FLFA_{cs}$ with real damage data, greater accuracy has been achieved, and the effects of damage reduction measures have been considered. The greater precision is clear by comparing the performance of the $FLFA_{rs}$ model with the outcomes of the Geoscience Australia (GA) depth-damage function and the USACE model from the USA. The statistical comparison has also been conducted for the $FLFA_{cs}$ model in contrast to the $FLEMO_{cs}$ model and the FEMA damage functions from overseas, as well as the ANUFLOOD damage model from Australia. Furthermore, numerical analysis was conducted to estimate the level of uncertainty and validate the applied damage models. The validation procedure shows very good results for $FLFA_{rs}$ and $FLFA_{cs}$ (i.e. low predictive error, low variation and acceptable reliability of results). These analyses show that the accuracy of results is dependent on model calibration, especially when the water depth is the only hydraulic parameter considered. Also, this study shows that the evaluated state methodologies are considerably overestimating the magnitude of flood impacts, or significantly underestimating the value of losses since they have not been calibrated with updated empirical loss data.

Chapter 8: Conclusions

- The newly derived relative stage-damage function also has a better level of transferability in time and space. The study has attempted to improve the accuracy and transferability of the model by moving away from a traditional approach (i.e. relying only on a deterministic relationship between the use of a flooded object and the stage of water) into a new approach which uses multi-parameters and probabilistic analysis. Accordingly, the study has illustrated a bootstrapping approach to the empirical data to consider the inherent uncertainty of the data set and to assist in describing confidence limits around the flood loss function parameters. The inherent uncertainty of the new model is a function of the knowledge (epistemic) uncertainty and the great variation in building characteristics. By this approach, the variability in real-world behaviours and the most likely relationship between the flooded properties' features and depth of water have been explored.
- The other advantage of the stage-damage functions is the simplicity with which its parameters can be changed based on building practices (different foundation height, ground elevation, damage percentages below ground, number of storeys, height of storeys, maximum damage as a percentage and the beginning elevation for damage) across the world. The method is simple enough to understand and generalise to other types of buildings and vulnerability classes. The validation procedure of the transferred model shows that estimates are good (no bias, 10% mean absolute error and 14% root mean square error), especially when the flood is deep (more than 60 cm) and its performance is acceptable. Also, its predictive capacity is significantly better than the Damage Scanner model used frequently in Europe.
- This study outcome shows that tree-based models are effective in identifying the significant damage-influencing factors and extracting the local relevance of every predictor. The result of the pruned tree shows that water depth, floor space, private precautionary measures, building value and building quality are the important damage predictors. Water depth is the most significant damage-influencing parameter, correlating positively with the loss ratio. Building floor space and building

Chapter 8: Conclusions

quality correlate negatively with the extent of losses, especially when the flood is deep (for water depths more than 64cm and more than 177.5cm, respectively). The private precaution measures correlate negatively with the loss ratio when the water depth is high. This finding is opposite to the outcome of the studies in Germany, where the effects of the precaution measures were significant for the shallow flood. The reason can be inferred based on the type of precaution measures considered and the flood characteristics. The other damage influencing parameter is building value. However, its correlation with the loss value is not specified. Other damage predictors (e.g. water contamination, flow velocity and socioeconomic status) might be found to correlate with the extent of losses if, regardless of the overfitting phenomena, an unpruned tree had been developed.

- Furthermore, the performance of tree-based models was compared with the newly derived flood loss function (FLFA). It was shown that the regression tree, which considers more details of the flood damage process, performs better (with fewer values for MAE and RMSE errors, and a higher correlation coefficient), and has a higher transferability across time and space. Also, there is a small improvement in the predictive capability and the reliability of the bagging decision tree compared to the regression tree. Accordingly, considering more damage-influencing parameters (especially the important factors stated in this research) and taking advantage of tree-based models are recommended.

In summary, this thesis presents a significant contribution to the flood damage assessment process by offering a calibrated and validated flood loss estimation framework. The accuracy, transferability and reliability have been enhanced, especially when the flood is deep, the extent of damage is more considerable, and the prediction performance of the model is more important. The results provide the input data for subsequent damage reduction, vulnerability mitigation and disaster risk reduction actions.

8.3 Recommendations for Future Work

- The focus of this research was on short duration riverine (low-velocity) inundation. Hence, further research on residential and non-residential stage-damage functions will be aimed at the evaluation of more flood impact parameters (high velocity, water salinity, long duration and high sediment load), incorporating more factors influencing exposure and vulnerability, and enhancing precision in damage documentation procedures.
- Although non-residential building losses are less about structural damage and more about damage to contents, due to limited availability of data, the FLFA_{cs} model has been built only for structural damage. However, the simplicity of the new function makes it possible to be developed in future research, even for use in another region of study. Also, since the vulnerability of commercial buildings to flood is of particular interest to the insurance industry, databases of insurance claims can benefit this research considerably. Therefore, reconciliation with insurance claims data and consideration of more flood loss events are recommended for future work. Finally, taking into account more variations in commercial sectors and evaluation of indirect losses is recommended.
- Further research on tree-based models will be aimed at examining a more comprehensive data set to explore the significance of other influencing factors (e.g. return period, long duration flooding, sediment loading and early warning). Overall, considering more details of the damaging process can be useful for improving the predictive capacity of flood damage prediction models and enhancing the level of transferability. In this regard, reliance on probability analysis can intensify the reliability of damage models, particularly when the models are used in different flooding events.

9 APPENDIX: PUBLICATIONS



Calibration and validation of FLFA_{rs} – a new flood loss function for Australian residential structures

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Abstract. Rapid urbanisation, climate change and unsustainable developments are increasing the risk of floods. Flood is a frequent natural hazard that has significant financial consequences for Australia. The emergency response system in Australia is very successful and has saved many lives over the years. However, the preparedness for natural disaster impacts in terms of loss reduction and damage mitigation has been less successful.

In this paper, a newly derived flood loss function for Australian residential structures (FLFA_{rs}) has been presented and calibrated by using historic data collected from an extreme event in Queensland, Australia, that occurred in 2013. Afterwards, the performance of the method developed in this work (contrasted to one Australian model and one model from USA) has been compared with the observed damage data collected from a 2012 flood event in Maranoa, Queensland. Based on this analysis, validation of the selected methodologies has been performed in terms of Australian geographical conditions.

Results obtained from the new empirically based function (FLFA_{rs}) and the other models indicate that it is apparent that the precision of flood damage models is strongly dependent on selected stage damage curves, and flood damage estimation without model calibration might result in inaccurate predictions of losses. Therefore, it is very important to be aware of the associated uncertainties in flood risk assessment, especially if models have not been calibrated with real damage data.

1 Introduction

Studies have shown that compared to other types of natural hazards, floods are a considerable threat to a nation's economy, the built environment, and people (André et al., 2013; Kourgialas and Karatzas, 2012; Llasat et al., 2014; UNISDR, 2009). Furthermore, in recent decades, the flood risk due to climate change and the growth in value and vulnerability of exposed properties has been increasing exponentially (Elmer et al., 2012; Kundzewicz et al., 2005), which subsequently raises the significance of flood risk management. Flood damage assessment in order to mitigate the probability of expected losses is an important part of the risk management process (André et al., 2013; Elmer et al., 2010; Kaplan and Garrick, 1981), and the results will provide decision-makers, emergency management organisations, and insurance and reinsurance companies with a tool for planning better risk mitigation strategies to cope with future disasters (Emanuelson et al., 2014; Merz et al., 2010).

In general, there is no common agreement among terms such as damage, loss and impact, but flood damage can either be categorised as direct or indirect. The direct category occurs due to physical contact between the floodwater and the inundated objects, and the indirect category is based on the effects of direct damage on a wider scale of space and time (Meyer et al., 2013; Molinari et al., 2014a; Thieken et al., 2005). Both categories can be evaluated as marketable (tangible) or non-marketable (intangible) values (André et al., 2013; Kreibich et al., 2010). The focus of this study is



Development and evaluation of FLFA_{CS} – A new Flood Loss Function for Australian commercial structures



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ABSTRACT

Commercial building flood losses significantly affect the Australian economy; however, there are not many models for commercial flood damage estimation and their results are not reliable. This study has attempted to derive and develop a new model (FLFA_{CS}) for estimating the magnitude of direct damage on commercial structures. The FLFA_{CS} – Flood Loss Function for Australian commercial structures, was calibrated using empirical data collected from the 2013 flood in Bundaberg, Australia, and considering the inherent uncertainty in the data sample. In addition, the newly derived model has been validated using a K-fold cross-validation procedure. The model performance has also been compared with the Flood Loss Estimation Model for the commercial sector (FLEMO_{CS}) and the Federal Emergency Management Agency (FEMA) damage functions from overseas, as well as the ANUFLOOD damage model from Australia.

The validation procedure shows very good results for FLFA_{CS} performance (no bias and only five per cent mean absolute error). It also shows that ANUFLOOD, as Australia's most prevalently used commercial loss estimation model, is still subject to very high uncertainty. Hence, there is an immediate need for a project to build new depth–damage functions for commercial and industrial properties.

Awareness of these issues is important for strategic decision-making in flood risk reduction and it could amplify the cognition of decision-makers and insurance companies about flood risk assessment in Australia.

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1. Introduction

Statistical analyses shows the considerable impacts of flood risk compared to other types of natural hazards [1,30,35,64]. In Australia, floods are the most costly of all disaster types, contributing 29% of the total cost for the nation's economy and the built environment [29,7]. Unfortunately, unsustainable developments and global warming are increasing the risk of flood [13,34,37]. Consequently, flood risk assessment and flood risk mitigation are gaining more attention [1,31,49].

Flood risk can be defined as the probability and magnitude of expected losses [1,14,27,31,47,48,63]. Therefore, loss estimation and consequence assessment is an indispensable part of flood risk assessment, and the results will provide decision-makers with an essential tool for planning better risk reduction strategies [15,18,37,39].

In general, flood losses can be categorised into direct or indirect [41,43,61]; and marketable (tangible) or non-marketable (intangible)

values [1,31,43]. Direct damages take place due to physical contact between the floodwater and inundated structures [23,37,46]. This study is limited to direct, tangible damages of commercial structures due to a short duration of riverine (low velocity) inundation.

In Australia, direct tangible damages of commercial buildings could be estimated by the Rapid Appraisal Method (RAM) or by function approaches (e.g. ANUFLOOD). Function approaches are the most common and internationally accepted methodology [23]. They make a causal relationship between the magnitude of the hazard and resistance of flooded objects, and can estimate the extent of losses for each stage of water [11,19,26,33,45,57,60]. Function approaches can be categorised into absolute and relative types. Absolute functions express the magnitude of damages in monetary values; while relative types estimate the dimension of losses as a ratio of the total value, i.e. replacement value or depreciated value [31]. Relative loss functions in contrast to absolute loss functions have better transferability in space and time since they are independent of changes in market values [39]. However, both types are restricted to the area of origin in terms of geographical conditions, i.e. building characteristics and flood specifications [37,50,8]. Therefore, the results of transferred models

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Flood loss modelling with FLF-IT: a new flood loss function for Italian residential structures

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Abstract. The damage triggered by different flood events costs the Italian economy millions of euros each year. This cost is likely to increase in the future due to climate variability and economic development. In order to avoid or reduce such significant financial losses, risk management requires tools which can provide a reliable estimate of potential flood impacts across the country. Flood loss functions are an internationally accepted method for estimating physical flood damage in urban areas. In this study, we derived a new flood loss function for Italian residential structures (FLF-IT), on the basis of empirical damage data collected from a recent flood event in the region of Emilia-Romagna. The function was developed based on a new Australian approach (FLFA), which represents the confidence limits that exist around the parameterized functional depth–damage relationship. After model calibration, the performance of the model was validated for the prediction of loss ratios and absolute damage values. It was also contrasted with an uncalibrated relative model with frequent usage in Europe. In this regard, a three-fold cross-validation procedure was carried out over the empirical sample to measure the range of uncertainty from the actual damage data. The predictive capability has also been studied for some sub-classes of water depth. The validation procedure shows that the newly derived function performs well (no bias and only 10 % mean absolute error), especially when the water depth is high. Results of these validation

tests illustrate the importance of model calibration. The advantages of the FLF-IT model over other Italian models include calibration with empirical data, consideration of the epistemic uncertainty of data, and the ability to change parameters based on building practices across Italy.

1 Introduction

Floods are the natural hazards that cause the largest economic impact in Europe today (European Environment Agency, 2010). Italy is no exception, with about 80 % of its municipalities being exposed to some degree of hydrogeological hazards (Zampetti et al., 2012). Regarding flood hazard frequency, 8 % of Italy's territory and 10 % of its population are exposed to a flood probability of once every 100 to 200 years (ANCE/CRESME, 2012; Trigila et al., 2015). This issue is reflected in over a billion euros spent from 2009 to 2012 on recovery from extreme hydrological events (Zampetti et al., 2012). Italy is, in fact, the European country where floods generate the largest economic damage per annum (Alfieri et al., 2016). This is especially worrisome considering that the frequency of extreme flood losses may be doubled at least by 2050 in Europe due to climatic change factors and urban expansion (Jongman et al., 2014). Climate variability already affects rainfall extremes and the peak vol-

Article

An Assessment of the Effectiveness of Tree-Based Models for Multi-Variate Flood Damage Assessment in Australia

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Abstract: Flood is a frequent natural hazard that has significant financial consequences for Australia. In Australia, physical losses caused by floods are commonly estimated by stage-damage functions. These methods usually consider only the depth of the water and the type of buildings at risk. However, flood damage is a complicated process, and it is dependent on a variety of factors which are rarely taken into account. This study explores the interaction, importance, and influence of water depth, flow velocity, water contamination, precautionary measures, emergency measures, flood experience, floor area, building value, building quality, and socioeconomic status. The study uses tree-based models (regression trees and bagging decision trees) and a dataset collected from 2012 to 2013 flood events in Queensland, which includes information on structural damages, impact parameters, and resistance variables. The tree-based approaches show water depth, floor area, precautionary measures, building value, and building quality to be important damage-influencing parameters. Furthermore, the performance of the tree-based models is validated and contrasted with the outcomes of a multi-parameter loss function (FLFA_{rs}) from Australia. The tree-based models are shown to be more accurate than the stage-damage function. Consequently, considering more parameters and taking advantage of tree-based models is recommended. The outcome is important for improving established Australian flood loss models and assisting decision-makers and insurance companies dealing with flood risk assessment.

Keywords: flood damage assessment; flood risk; stage-damage function; multi-variate analysis; flood loss-influencing parameters; tree-based analyses; FLFA_{rs}; risk reduction

1. Introduction

In recent decades, flood risk is growing, due to climate change and increase in vulnerability of properties at risk [1–3]. In Australia, floods are the most costly of all disaster types [4], contributing 29% of the total cost of the nation's economy and the built environment [5,6]. Accordingly, flood risk management is attracting more attention [7–9], and results are used to inform disaster management policy and support the development of risk reduction measures [10,11]. Flood risk management has to be based upon an appropriate evaluation of flood hazard and flood vulnerability [12,13], including an assessment of damage and effectiveness of risk reduction measures [14–16]. Therefore, loss estimation and consequence assessment is an indispensable part of flood risk management [17,18]. However,

Predictive applications of Australian flood loss models after a temporal and spatial transfer

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ABSTRACT

In recent decades, considerably greater flood losses have increased attention to flood risk evaluation. This study used data-sets collected from Queensland flood events and investigated the predictive capacity of three new Australian flood loss models to assess the extent of physical damages, after a temporal and spatial transfer. The models' predictive power is tested for precision, variation, and reliability. The performance of a new Australian flood loss function was contrasted with two tree-based damage models, one pruned and one un-pruned. The tree-based models are grown based on the interaction of flood loss ratio with 13 examined predictors gathered from flood specifications, building characteristics, and mitigation actions. Besides an overall comparison, the prediction capacity is also checked for some sub-classes of water depth and some groups of building-type.

It has been shown that considering more details of the flood damage process can improve the predictive capacity of damage prediction models. In this regard, complexity with parameters with low predictive power may lead to more uncertain results. On the other hand, it has also been demonstrated that the probability analysis approach can make damage models more reliable when they are subjected to use in different flooding events.

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1. Introduction

Flood is a common natural disaster in Australia, and a frequently occurring natural phenomenon in the world (Baeck et al. 2014; Hasanzadeh Nafari et al. 2015; Bhatt et al. 2016). In recent decades, flood impacts have increased (Kreibich et al. 2007; Cheng and Thompson 2016; McMillan et al. 2016; Mojaddadi et al. 2017), reaching 29% of the total cost of Australian natural disasters (Bureau of Transport Economics 2001). Hence, flood risk evaluation including hazard assessment and estimation of the associated consequences (Ciullo et al. 2016; Vojtek and Vojteková 2016) has attracted growing attention (Raaijmakers et al. 2008; Merz et al. 2010; Cammerer et al. 2013; Kundzewicz et al. 2013). While much effort has gone into hazard investigation, i.e. models of probability and intensity of flood, flood loss estimation models are still subject to a high level of uncertainty (Merz et al. 2004; Kreibich and Thielen 2008; Meyer et al. 2013). Loss estimation is needed in cost–benefit analyses of disaster risk reduction measures (Mechler 2016), vulnerability and resilience studies, flood risk analyses, and in the insurance and reinsurance sectors (de Moel and Aerts 2011).

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