FLOOD RISK ASSESSMENT USING MULTI-SENSOR REMOTE SENSING, GEOGRAPHIC INFORMATION SYSTEM, 2D HYDRAULIC AND MACHINE LEARNING BASED MODELS

By

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A Thesis Submitted in Fulfilment of the degree of **Doctor of Philosophy**



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CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I, Hossein Mojaddadi Rizeei declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctoral of Philosophy, in the FEIT at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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DEDICATION

This thesis is dedicated to my Father.

In memory of Mohammad Reza Mojaddadi Rizeei. You left fingerprints of grace on my life. You shan't be forgotten. May God almighty bless you.

ACKNOWLEDGEMENT

Praise belongs to God, the Lord of the world who inspires me everywhere.

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LIST OF PAPERS/PUBLICATIONS

Published journal articles

- 1. **Rizeei, H. M.**, Pradhan, B., Saharkhiz, M. A. (2018). Urban object extraction using Dempster Shafer Feature Based Image Analysis from Worldview-3 satellite imagery. *International journal of remote sensing*. https://doi.org/10.1080/01431161.2018.1524173
- 2. **Rizeei, H. M.**, Pradhan, B., Saharkhiz, M. A. (2018). Surface runoff prediction regarding LULC and climate dynamics using coupled LTM, optimized ARIMA, and GIS-based SCS-CN models in tropical region. *Arabian Journal of Geosciences*, 11(3), 53. https://doi.org/10.1007/s12517-018-3397-6
- 3. **Rizeei, H. M**., Pradhan, B., Saharkhiz, M. A. (2018). An integrated fluvial and flash pluvial model using 2D high-resolution sub-grid and particle swarm optimization-based random forest approaches in GIS. *Complex & Intelligent Systems*, 1-20. https://doi.org/10.1007/s40747-018-0078-8
- 4. **Mojaddadi, H.**, Pradhan, B., Nampak, H., Ahmad, N., & Ghazali, A. H. B. (2017). Ensemble machine-learning-based geospatial approach for flood risk assessment using multi-sensor remote-sensing data and GIS. *Geomatics, Natural Hazards and Risk*, 1-23. http://dx.doi.org/10.1080/19475705.2017.1294113.

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All the aforementioned papers have been published during my PhD candidature.

LIST OF ABBREVIATIONS

Symbol	Description
AHP	Analytical Hierarchy Process
LTM	Land Transformation Model
ANN	Artificial Neural Network
HRS	High Resolution Sub-grid
AUC	Area Under Curve
BSA	Bivariate Statistical Analysis
DEM	Digital Elevation Model
DT	Decision Tree
EBF	Evidential Belief Function
FIS	Fuzzy Interface System
FR	Frequency Ratio
GIS	Geographic Information System
LN	Linear
LR	Logistic Regression
LULC	Land use/cover

MSA	Multivariate Statistical Analysis
NDVI	Normalized Difference Vegetation Index
PL	Polynomial
POF	Plateau Objective Function
RBF	Radial Basis Function
RS	Remote Sensing
InSAR/IFSAR	Interferometric Synthetic Aperture Radar
SIG	Sigmoid
SPI	Stream Power Index
SVM	Support Vector Machine
TRI	Topographic Roughness Index
TWI	Topographic Wetness Index
PSO	Particle Swarm Optimization
ARIMA	Autoregressive Integrated Moving Average
SCS	Soil Conservation Service
CN	Curve Number
FBIA	Feature Based Image Analysis

PBIA Pixel Based Image Analysis OBIA Object Based Image Analysis FPP Flash Pluvial Flood FF Fluvial Flood RF Random Forest DSM Digital Surface Model ROC Receiver Operating Characteristic **RMSE** Root Mean Square Error

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ABSTRACT

Flooding events threaten the population, economy and environment worldwide. In recent years, several spatial methods have been developed to map flood susceptibility, hazard and risk for predicting and modelling flooding events. However, this research proposes multiple state-of-the-art approaches to assess, simulate and forecast flooding from recent satellite imagery.

Firstly, a model was proposed to monitor changes in surface runoff and forecast future surface runoff on the basis of land use/land cover (LULC) and precipitation factors because the effects of precipitation and LULC dynamics have directly affected surface runoff and flooding events. Land transformation model (LTM) was used to detect the LULC changes. Moreover, an autoregressive integrated moving average (ARIMA) model was applied to analyse and forecast rainfall trends. The parameters of the ARIMA time series model were calibrated and fitted statistically to minimise prediction uncertainty through modern Taguchi method. Then, a GIS -based soil conservation service-curve number (SCS-CN) model was developed to simulate the maximum probable surface runoff. Results showed that deforestation and urbanisation have occurred upon a given time and have been predicted to increase. Furthermore, given negative changes in LULC, surface runoff increased and was forecasted to exceed gradually by 2020. In accordance with the implemented model calibration and accuracy assessment, the GIS-based SCS-CN combined with the LTM and ARIMA model is an efficient and accurate approach to detecting, monitoring and forecasting surface runoff.

Secondly, a physical vulnerability assessment of flood was conducted by extracting detailed urban features from Worldview-3. Panchromatic sharpening in conjunction with atmospheric and topographic corrections was initially implemented to increase spatial resolution and reduce atmospheric distortion from satellite images. Dempster—Shafer (DS) fusion classifier was proposed in this part as a feature-based image analysis (FBIA) to extract urban complex objects. The DS-FBIA was investigated among two sites to examine the transferability of the proposed method. In addition, the DS-FBIA was compared with other common image analysis approaches (pixel- and object-based image analyses) to discover its accuracy and computational operating time. k-nearest neighbour, Bayes and support vector machine (SVM) classifiers were tested as pixel-based image analysis approaches, while decision tree classifier was examined as an object-based image analysis approach. The results showed improvements in detailed urban extraction obtained using the proposed FBIA with 92.2% overall accuracy and with high transferability from one site to another.

Thirdly, an integrated model was developed for probability analysis of different types of flood using fully distributed GIS-based algorithms. These methods were applicable, particularly where annual monsoon rains trigger fluvial floods (FF) with pluvial flash flood (PFF) events occur simultaneously. A hydraulic 2D high-resolution sub-grid model of hydrologic engineering centre river analysis system was performed to simulate FF probability and hazard. Moreover, machine learning random forest (RF) method was used to model PFF probability and hazard. The RF was optimised by particle swarm optimisation (PSO) algorithm. Both models were verified and calibrated by cross

validation and sensitivity analysis to create a coupled PFF– FF probability mapping. The results showed high accuracy in generating a coupled PFF–FF probability model that can discover the impact and contribution of each type to urban flood hazard. Furthermore, the results provided detailed flood information for urban managers to equip infrastructures, such as highways, roads and sewage network, actively.

Fourthly, the risk of a flood can be assessed through different stages of flood probability, hazard and vulnerability. A total of 13 flood conditioning parameters were created to construct a geospatial database for flood probability estimation in two study areas. To estimate flood probability, five approaches, namely, logistic regression, frequency ratio (FR), SVM, analytical hierarchy process and combined FR–SVM, were adopted. Then, a flood risk map was generated by integrating flood hazard and vulnerability. The accuracy of flood probability indices indicated that the combined FR–SVM method achieved the highest accuracy among the other approaches. The reliability of the results obtained from this research was also verified in the field. The most effective parameters that would trigger flood occurrence were rainfall and flood inundation depth.

In this research, transferable residency from one study area to another was verified through all the implemented methods. Therefore, the proposed approaches would be effectively and easily replicated in other regions with a similar climate condition, that condition that is, having a sufficient amount of flooding inventory events. Moreover, the results of the proposed approaches provided solid-detailed information that would be used for making favourable decisions to reduce and control future flood risks.