

# **UNIVERSITI PUTRA MALAYSIA**

FLOOD MODELLING USING AN INTEGRATED ARTIFICIAL NEURAL NETWORK AND NEURO-FUZZY TECHNIQUE FOR JOHOR RIVER BASIN, MALAYSIA

# MASOUD BAKHTYARI KIA

FK 2013 113



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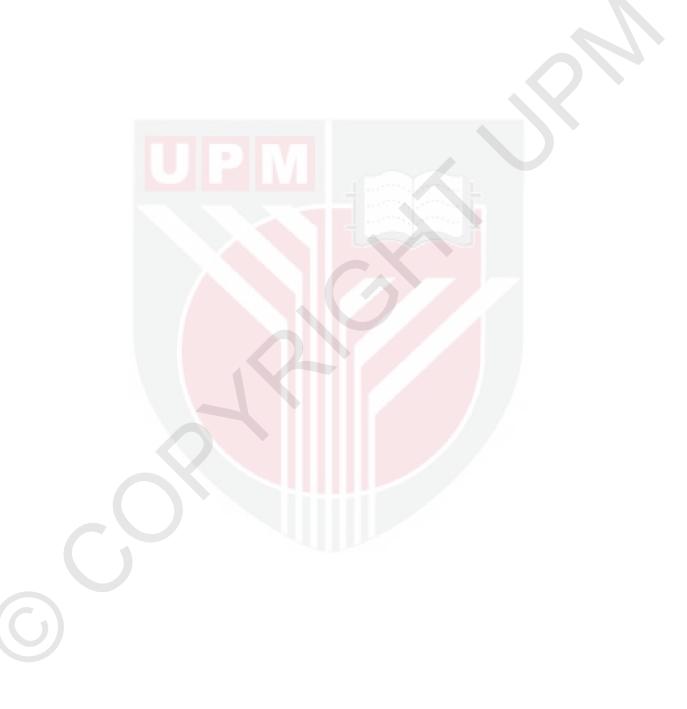


MASOUD BAKHTYARI KIA

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

August 2013

This thesis is dedicated to my wife and children who have always stood by me, and to the soul of my father may Allah bless him and grant him peace.



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

## FLOOD MODELLING USING AN INTEGRATED ARTIFICIAL NEURAL NETWORK AND NEURO-FUZZY TECHNIQUE FOR JOHOR RIVER BASIN, MALAYSIA

By

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August 2013

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Flooding is one of the most destructive natural hazards that cause damage to both life and property every year, and therefore the development of flood model to determine inundation area in watersheds is important for decision makers. In recent years, data mining approaches such as artificial neural network (ANN) and Neuro-Fuzzy techniques are being increasingly used for flood modeling. Previously, these methods were frequently used for hydrological and flood modeling by taking rainfall as input and runoff data as output, usually without taking into consideration of other flood causative factors. The specific objective of this study is to develop a flood model using various flood causative factors by Multilayer Perceptron neural network (*MLP*) and Local Linear Model Tree (LOLIMOT) techniques, and geographic

information system (GIS) to modeling and simulate flood-prone areas in the southern part of Peninsular Malaysia. The ANN and Neuro-Fuzzy models for this study were developed in MATLAB using seven flood causative factors. Relevant thematic layers (including rainfall, slope, elevation, flow accumulation, soil, land use, and geology) are generated using GIS, and field surveys. In the context of objective weight assignments, the ANN is used to directly produce water levels and then the flood map is constructed in GIS. Comparison between the forecasted and observed river flow indicate that the accuracy of models are quite good especially in ANN model. The flood inundation area is derived based on this model by using DEM map. To measure the performance of the model, four criteria performances, including a coefficient of determination (R<sup>2</sup>), the sum squared error, the mean square error, and the root mean square error are used. The verification results showed satisfactory agreement between the predicted and the real hydrological records. The sensitivity analysis performed shows that with the exception of the rainfall factor as the main reason of floods, the elevation is the most important factor and geology has the least influence on river flow. The study is first attempt to use these integration methods in the flood modeling that used different causative factors. The results of this study could be used to help local and national government plan for the future and develop appropriate (to the local environmental conditions) new infrastructure to protect the lives and property of the people of Johor.

Key Words: Flood, GIS, Spatial Modeling, Neural Networks, Neuro-Fuzzy

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

### PEMODELAN BANJIR MENGGUNAKAN BERSEPADU RANGKAIAN NEURAL TIRUAN DAN NEURO-SAMAR TEKNIK UNTUK JOHOR LEMBANGAN SUNGAI, MALAYSIA



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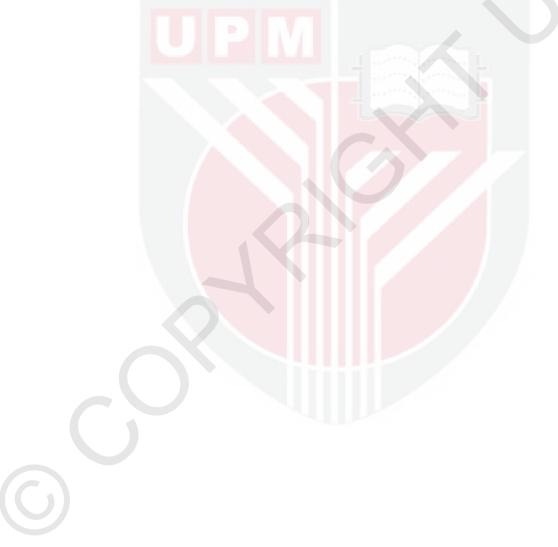
Banjir adalah salah satu bencana alam yang paling merosakkan yang menyebabkan kerosakan kepada kedua-dua nyawa dan harta benda setiap tahun, dan oleh itu pembangunan model banjir untuk menentukan kawasan banjir di kawasan tadahan air adalah penting bagi pembuat keputusan. Dalam tahun-tahun kebelakangan ini, perlombongan data pendekatan seperti rangkaian neural tiruan (ANN) dan teknik Neuro-kabur menjadi semakin digunakan untuk pemodelan banjir. Sebelum ini, kaedah ini telah sering

digunakan untuk model hidrologi dan banjir dengan mengambil hujan sebagai input dan data air larian sebagai output, biasanya tanpa mengambil kira faktor-faktor lain penyebab banjir. Objektif khusus kajian ini adalah untuk membangunkan model banjir menggunakan pelbagai faktor penyebab banjir oleh Multilayer Perceptron rangkaian neural (MLP) dan Tempatan Linear Model Tree (LOLIMOT) teknik, dan sistem maklumat geografi (GIS) untuk pemodelan dan simulasi kawasan banjir di bahagian selatan Semenanjung Malaysia. ANN dan Neuro-kabur model untuk kajian ini telah dibangunkan pada MATLAB menggunakan tujuh faktor penyebab banjir. Lapisan tema yang berkaitan (termasuk hujan, cerun, ketinggian, pengumpulan aliran, tanah, guna tanah, dan geologi) dihasilkan menggunakan GIS, dan bidang kaji selidik. Dalam konteks tugasan berat objektif, ANN digunakan untuk terus menghasilkan tahap air dan kemudian peta banjir itu dibina dalam GIS. Perbandingan antara aliran diramalkan dan memerhatikan sungai menunjukkan bahawa ketepatan model yang agak baik terutamanya dalam model ANN. Kawasan banjir banjir berasal berdasarkan model ini dengan menggunakan peta DEM. Untuk mengukur prestasi model, empat kriteria persembahan, termasuk pekali penentuan (R<sup>2</sup>), kesilapan jumlah kuasa dua, ralat kuasa dua min, dan punca min ralat kuasa dua digunakan. Keputusan pengesahan menunjukkan persetujuan vang memuaskan antara yang diramalkan dan rekod hidrologi sebenar. Analisis sensitiviti dilakukan menunjukkan bahawa kecuali faktor hujan sebagai sebab utama banjir, ketinggian adalah faktor yang paling penting dan mempunyai pengaruh geologi sekurang-kurangnya ke atas aliran sungai. Kajian ini merupakan percubaan pertama untuk menggunakan kaedah integrasi dalam

iv

pemodelan banjir yang digunakan faktor penyebab yang berbeza. Hasil kajian ini boleh digunakan untuk membantu rancangan kerajaan tempatan dan nasional untuk masa depan dan membangunkan yang sesuai (dengan syarat-syarat alam sekitar tempatan) infrastruktur baru untuk melindungi nyawa dan harta benda rakyat Johor.

Kata Kunci: Banjir, GIS, PemodelanRuang, neural tiruan, Neuro-kabur.



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vi

I certify that a Thesis Examination Committee has met on 9th May 2013 to conduct the final examination of MasoudBakhtyari Kia on his thesis entitled "FLOOD MODELLING USING AN INTEGRATED ARTIFICIAL NEURAL NETWORK AND NEURO-FUZZY TECHNIQUE FOR JOHOR RIVER BASIN, MALAYSIA" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy degree.

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## DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at University Putra Malaysia or at any other institutions.



## TABLE OF CONTENTS

	Page
ABSTRACT ABSTRAK ACKNOWLEDGEMENTS DECLARATION LIST OF TABLES LIST OF FIGURES	i iii vi ix xii xii xiv
CHAPTER	
1. INTRODUCTION	1
<ul> <li>1.1 Overview</li> <li>1.2 Research Problem</li> <li>1.3 Significance of Research</li> <li>1.4 Research Objectives</li> <li>1.5 Scope of Research</li> <li>1.6 Thesis Organization</li> </ul>	1 3 6 7 8 8
2. LITEATURE REVIEW	11
<ul> <li>2.1 Introduction</li> <li>2.2 What is a model? <ul> <li>2.2.1 Application of Model in Hydrology</li> <li>2.2.2 Steps in Flood Modeling</li> <li>2.2.3 Flood factors</li> </ul> </li> <li>2.3 Overview of hydrological model for flood modeling <ul> <li>2.3.1 Main types of Hydrological Models</li> <li>2.3.2 Application of Soft Computing in Modeling</li> </ul> </li> <li>2.4 Needs to develop the models</li> <li>2.5 Flood Problem in Malaysia</li> <li>2.6 Summary</li> </ul>	11 11 12 14 15 20 20 31 60 66 70
3. MATERIALS AND METHODS	71
<ul> <li>3.1 INTRODUCTION</li> <li>3.2 Study area and Materials <ul> <li>3.2.1 Coordinate System</li> <li>3.2.2 Thematic data layer preparation</li> </ul> </li> <li>3.3 Methodology <ul> <li>3.3.1 Model parameters coincidence analyses</li> <li>3.3.2 ANN Method</li> <li>3.3.3 Neuro-Fuzzy</li> </ul> </li> <li>3.4 Performance assessment <ul> <li>3.4.1 Coefficient of determination</li> <li>3.4.2 Sum Squared Error (SSE)</li> </ul> </li> </ul>	71 71 75 75 86 88 118 128 137 137

	3.4.4 Root Mean Square Error	139
4. RES	ULTS AND DISCUSSION	140
4.1	Introduction	140
4.2	Results of ANN model	140
	4.2.1 Testing the Network	149
4.3	Results of Neuro-Fuzzy	150
4.4	Performance evaluation	157
4.6	Model performance assessments	164
4.7	Discussion	166
4.8	Summary	169
5. CON	CLUSIONS AND RECOMMENDATIONS	170
5.1	Conclusions	170
5.2	New finding and research contribution	171
	5.2.1 Providing learning algorithms to enhance the performa	ance of
	the ANN and Neuro-Fuzzy flood models	171
	5.2.2 Identification and ranking of the most causative flood f	actors
	to flood mitigation in study area by using sensitivity;	171
	5.2.3 Integration the ANN and Neuro-Fuzzy with GIS in floor	
	modeling	172
	5.2.4 Development of new spatial flood model	173
	5.2.5 Providing flood map	173
5.3	Recommendations for Future Research	174
REFER	ENCES	176
Append	A xib	195
Append		199
	TA OF STUDENT	213

 $\mathbb{G}$ 

## LIST OF TABLES

Table	Page
2. 1 Flood contributing factors	19
2. 2 Comparison of ANN and Fuzzy Logic	51
3. 1 Classification of slopes in Johor River Basin	79
3. 2 Land use characteristics of Johor River Basin	84
3. 3 Summary of the rain gauges of Johor River Basin	85
3. 4 Weights of thematic layers and their categories	87
3. 5 Mutual occurrence of slope and soil in the basin	90
3. 6 Mutual occurrence of land use and soil in the basin	92
3. 7 Mutual occurrence of flow accumulation and soil in the basin	94
3. 8 Mutual occurrence of soil and elevation in the basin	96
3. 9 Mutual occurrence of soil and geology in the basin	98
3. 10 Mutual occurrence of slope and land use in the basin	100
3. 11 Mutual occurrence of slope and flow accumulation in the basin	102
3. 12 Mutual occurrence of slope and elevation in the basin	104
3. 13 Mutual occurrence of slope and geology in the basin	106
3. 14 Mutual occurrence of land use and flow accumulation in the basi	n 108
3. 15 Mutual occurrence of land use and elevation in the basin	110
3. 16 Mutual occurrence of elevation and flow accumulation in the bas	in 112
3. 17 Mutual occurrence of elevation and geology in the basin	114
3. 18 Mutual occurrence of geology and flow accumulation in the basir	า 116
3. 19 Different ANN architectures and their errors during the training s	tep 126
3. 20 The neurons number and their MSE in LOLIMOT model	136
4. 11 Input (I) - Hidden Layer 1 (HA) connection weights	145

4. 2 Hidden layer 1 (HA)- Hidden Layer 2 (HB) connection weight	146
4. 3 Hidden layer 2 (HB)- Output layer connection weights	146
<ol> <li>4 The connection weights between input and hidden layer in LOLIMOT model</li> </ol>	152
4. 5 The connection weights between hidden layer and output layer in LOLIMOT model	152
4. 6 Comparison of model performance for MLP and LOLIMOT in training and testing	157
4. 7 Simulated the flood at Kota Tinggi during January 2007	161
4.8 Comparison of model performance for MLP during training and testing	165
4. 9 Sensitivity analysis results for the input factors	166

6

## LIST OF FIGURES

Figure	Page
1. 1 Regional distribution of disasters by type during 1970-2011	2
1. 2 World distribution of disasters by type during 1970-2011	2
1. 3 Schematic representation of the Thesis	10
2. 1 Phases in flood modeling as part of flood	15
2. 2 Causes of floods and flood-intensifying factors	18
2. 3 Classification of models based on Process, Scale, and Technique of solution	22
2. 4 Hybridization in Soft Computing	33
2. 5 Biological neuron and its principal components	37
2. 6 A typical ANN node architecture	39
2. 7 Sigmoid function	43
2. 8 Supervised Learning model	45
2. 9 Configuration of basic fuzzy logic controller	49
2. 10 Topology of LOLIMOT model	54
2. 11 Operation of the LOLIMOT algorithm in the first four iterations for a two-dimensional input space	59
2. 12 Flood prone area in west and east of Malaysia	67
3. 1 Location of the study area	73
3. 2 Digital Elevation Model (DEM) of Johor River Basin	78
3. 3 Classification of slopes in Johor River Basin	78
3. 4 Flow Direction map of Johor River Basin	80
3. 5 Flow Accumulation of Johor River Basin	80
3. 6 Lithology (Geological) map of study area	82

3.78	Spatial distribution of major soil types in the watershed	83
3. 8 L	and use map of Johor River Basin	84
3.9	Location of Rainfall Station	86
3. 10	Mutual occurrence of soil and slope in the basin	91
3. 11	Soil and slope coincidence and their effect on the surface water	91
3. 12	Mutual occurrence of land use and soil in the basin	93
3. 13	Soil and land use coincidence and their effect on the surface water	93
3. 14	Mutual occurrence of soil and flow accumulation in the basin	95
3. 15	Soil and flow accumulation coincidence and their effect on the surface water	95
3. 16	Mutual occurrence of soil and elevation in the basin	97
3. 17	Soil and elevation coincidence and their effect on the surface water	97
3. 18	Mutual occurrence of soil and geology in the basin	99
3. 19	Geology and soil coincidence and their effect on the surface water	99
3. 20	Mutual occurrence of slope and land use in the basin	101
3. 21	Slope and land use coincidence and their effect on the surface water	101
3. 22	Mutual occurrence of slope and flow accumulation	103
3. 23	Slope and flow accumulation coincidence and their effect on the surface water	103
3. 24	Mutual occurrence of slope and elevation in the basin	105
3. 25	Slope and elevation coincidence and their effect on the surface water	105
3. 26	Mutual occurrence of slope and geology	107
3. 27	Slope and geology coincidence and their effect on the surface water	107
3. 28	Mutual occurrence of land use and flow accumulation	109
3. 29	Land use and flow accumulation coincidence and their effect on	109

the surface water

3. 30 Mutual occurrence of land use and elevation in the basin	111
3. 31 Land use and elevation coincidence and their effect on the surface water	111
3. 32 Mutual occurrence of elevation and flow accumulation in the basin	113
3. 33 Elevation and flow accumulation coincidence and their effect on the surface water	113
3. 34 Mutual occurrence of elevation and geology in the basin	115
3. 35 Elevation and geology coincidence and their effect on the surface water	115
3. 36 Mutual occurrence of geology and flow accumulation in the basin	117
3. 37 Geology and Flow accumulation coincidence and their effect on the surface water	117
3. 38 Flow diagram showing different steps of ANN black box procedure	121
3.39 A schematic architecture of ANN for flood modeling	123
3.40 Flow chart showing weight determination of flood factors using ANN model	125
3. 41 The architecture of local linear model tree (LOLIMOT)	132
3.42 The LOLIMOT training flowchart for determination of weights	134
3.43 Training and testing process results in LOLIMOT	135
4. 1 The work Space of MATLAB software	141
4. 2 The Process of training in MATLAB	142
4. 3 The learning rate for the network	143
4. 4 Comparison of observed and predicted in training step	148
<ol><li>5 The regression plot between network outputs and network targets in training step</li></ol>	148
4. 6 Comparison of observed and predicted in testing step	149
4.7 The regression plot between network outputs and network targets in testing step	150

<ol> <li>8 Comparison of observed and predicted data in training step in LOLIMOT model</li> </ol>	154
<ol> <li>9 The regression plot between observed and predicted data in LOLIMOT modeling in testing step</li> </ol>	154
4. 10 Comparison plot between observed and predicted data in testing step	156
4. 11 The regression plot between observed and predicted data in testing step	156
4. 12 The MLP and LOLIMOT forecasted river flows versus observed for Rantau Panjang station	158
4.13 Scatter plot of observed versus LOLIMOT models predicted river flow	159
4.14 Scater plot of observed versus MLP models predicted river flow	159
4. 15 Flood at Johor river basin in January 2007 and comparing with flood of December 2006	162
4. 16 Comparison of simulated flood hydrographs with observed hydrographs at the Kota Tinggi gauging stations	162
4. 1 Flood inundation area in January 2007 at Johor river basin	163

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### **CHAPTER 1**

### INTRODUCTION

In this chapter, the background and motivation of the study are introduced. The limitations of flood modeling are stated in the problem statement, and indicate to potential application of new methods to create and develop flood models and flood susceptible areas. The aims and significance of the study are described and, finally, the study objectives and thesis framework are provided.

#### 1.1 Overview

Flooding is one of the most destructive and common natural hazards that cause damage to both life and property in many parts of the world every year. According to Center for Research on the Epidemiology of Disasters report (Sapir et al., 2012), floods were the most reported hazards, accounting for 33 percent of all disasters in the period 1970-2011 (Figures 1.1 and 1.2). Over this period and particularly the last decade, occurrence of floods has increased strongly due to economic developments, urbanization, climate change and other factors (Kenyon and Shannon, 2008; Huntington, 2006).

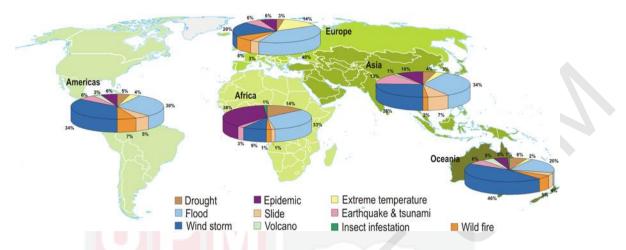


Figure 1.1: Regional distribution of disasters by type during 1970-2011 (Sapir et al., 2012)

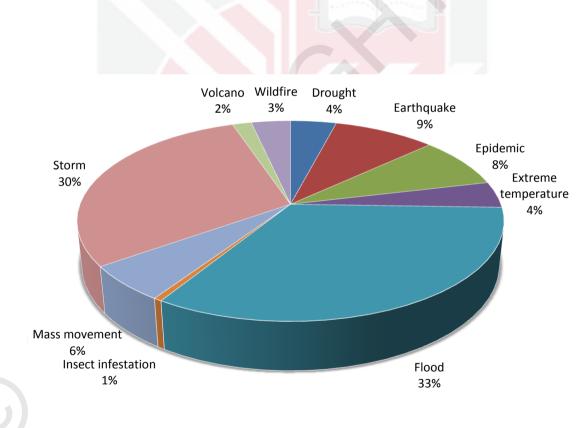


Figure 1. 2: World distribution of disasters by type during 1970-2011 (Sapir et al., 2012).

Floods are part of nature. This type of hazard is a historic problem that occurs often in different places in the world and will extend in the future. It is impossible to prevent and control flood events completely. Modeling, prediction and warning of floods without a doubt are the main task and challenge in hydrology (Thierion et al., 2011). This common disaster needs to systematic methods and developed the models to mitigation of damages. Many efforts have been done to predict, reduce and mitigation of floods by researchers and many models have been made in response to this need. The models are tools which help to understand how hydrological processes work, and improve the ability for successful flood forecasting and mitigation of damages. Although there are many models being developed and employed for flood forecasting, the main problem and challenge is remaining in this task.

### **1.2 Research Problem**

Flood disaster has a very special place in Malaysia. In this country, floods are the most important natural hazards in terms of population affected, frequency, area extent, and social economic damage. According to Ministry of Natural Resources and Environment (2007), flood prone areas cover 9% of land area ( $30000 \text{ km}^2$ ) in the country, and 22% of the population (5 million) is affected by floods. The annual average flood damage is more than RM 1 billion. There are several reports on floods in Johor river basin since 1981. According to the Ministry of Natural Resources and Environment reports, Johor river basin has experienced big floods, especially in the years of 1981, 1983, 1984, 1986, 1987, 1989, 1990, 1994, 1998, 2000, 2001. In December 2006 and January 2007, Johor state was affected by two major flood events which are considered as the most costly flood events in Malaysian history. During these floods, more than 100,000 people were evacuated, 18 persons were killed and the costs of losses are estimated about RM 1.5 billion (Ministry of Natural Resources and Environment, 2007).

To manage and control flood, Malaysian government has established about 335 telemetric rain gauges and 208 telemetric water level stations in the vicinity of 40 river basins for real time flood monitoring. The government also developed space technology to use remote sensing data for natural resources and environmental management in 1990s. Different hydrological models include physical and conceptual models also have been used to predict and flood simulation. Thus, currently, hydrological and meteorological data are collected real time, different high resolution satellite data to meet more effective environmental monitoring and natural resources management are received near real time, the best hardware and software are used to analysis the data. Nevertheless, flooding occurs repeatedly every year in various parts of the country, destroying property and killing people each year (Pradhan 2010).

4

The current method of flood warning in Johor state is based on a relationship between rainfall and runoff and ignored other flood causes factors. Exception of rainfall factor as the main reason, flood is affected by several factors such as land use, duration of the rainfall, initial soil moisture, geology, land use, evaporation, watershed infiltration, geomorphology, and so on. The effects of these factors are well known separately, but combination of them and interaction effects are less. To flood mitigation and reduce the losses, authorities and the general public should know these factors and role of each one in flood occurrence. This issue has not been done yet in details for study area.

The second problem is related to the deficiency of available flood models to use and definition of these factors. Since flood events and river flow nature are inherently uncertain, nonlinear and complex, it is impossible to predict flood frequency, water volume, and flood prone areas using available flood models by using all incorporate factors in catchments.

Many researchers have used different techniques with different factors, scales, accuracy for modeling. There is not standardized agreed model for simulate rivers behavior and preparing flood susceptibility maps in basins (Aronica et al. 2012).

In recent years, development of information processing, machine learning, and advances in the field of remote sensing and geographic information system (GIS) have greatly facilitated the operation of flood mapping and flood risk assessment. Apart from these tools, some works on fuzzy set methods (Luchetta and Manetti, 2003; Blazkova and Beven, 2004; Maskey et al., 2004; Ercanoglu and Gokceoglu, 2004; Akter and Simonovic, 2005), artificial neural networks (ANN) models (Brath *et al.*, 2002; Shrestha et al., 2005; Piotrowski et al., 2006; Peters et al., 2006), and Neuro-Fuzzy models (Dixon ,2004; Mahabir et al., 2006) have been attempted for flood modeling studies. These techniques in hydrology and flood studies used to calculate amount of runoff and determine relationship between rainfall and runoff in some basins. Since recognition, evaluation and modeling of hydrological processes in basins need to various information and knowledge about the models, techniques, and the study area (Merz et al., 2008; Aronica, G.T., et al., 2011) it seems these techniques can be improved by using more information and parameters in the modeling.

Due to some success of neural networks and fuzzy set theories, this research attempted to develop an objective procedure that take into account the advantages of GIS, ANN, and Neuro-Fuzzy theory (Spatial Neuro-Fuzzy) for flood modeling zonation in study area.

## 1.3 Significance of Research

Protection of the lives and properties from floods is of high priority for decision makers. Despite the significant costs to forecasting the floods,floods

still affect several parts, destroy properties, and kill people each year increasingly. Flood events are unavoidable, and the problem is not whether the next flood will occur or not (Maidment, 2002), but to reduce the losses, authorities and peoples should know when and where will they happen and which part of the area affected by floods.

In order to estimate precise flood risks, accurate flood model and mapping flood prone area are needed. Using new methods such as ANN and Fuzzy for precise prediction of river discharge, and capability of remote sensing and GIS techniques for monitoring and mapping of flooded areas, increase our ability to decrease these losses.

### 1.4 Research Objectives

The objective of this study was to improve a flood model using various flood causative factors using ANN, Neuro-Fuzzy technique and GIS to modeling and simulation of flood-prone areas at Johor River Basin, Malaysia. This is accomplished by:

 To create learning algorithms to enhance the performance of the ANN and Neuro-Fuzzy flood models;

- To apply, simulate, and compare the ANN and Neuro-Fuzzy flood models for simulation of water level and producing the flood map based on the best model;
- To determine and rank the most causative flood factors for flood mitigation in study area.

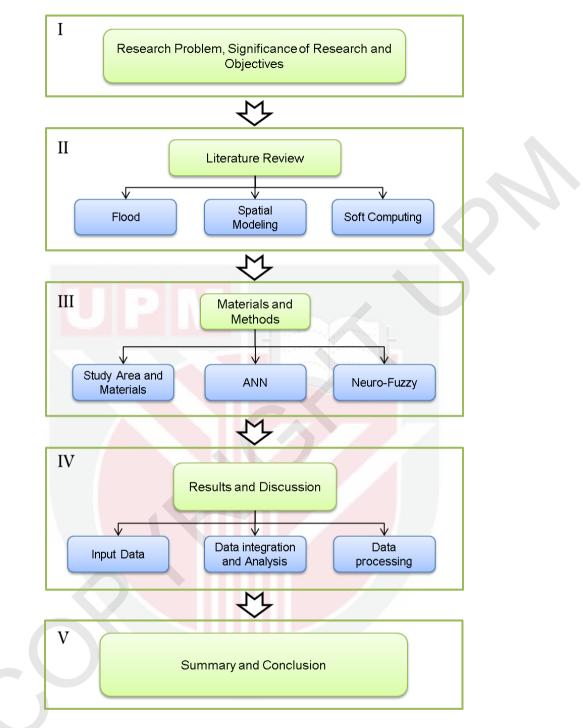
### 1.5 Scope of Research

This thesis enhances and examines two approaches to flood modeling and determine the influence of each factor on the flood. The first approach is based on a subdivision of artificial intelligence called artificial neural networks, the Multi-Layer Perceptron networks. The second is a combination of neural and fuzzy method, the Local Linear Model Tree (LOLIMOT) algorithm. The operation methods are developed and enhanced using the MATLAB software. After models accuracy assessment, the best models are used to flood simulation at Johor river basin. Each of these approaches will be explained in detail in the following chapters.

### **1.6 Thesis Organization**

The thesis comprises of five chapters, including this introductory chapter, which describes the flood problems and the advantages of having an accurate flood model. The model and common types of hydrological and

flood models, and flood problems in Malaysia are reviewed in chapter two. Moreover, it looks at how new technologies such as GIS, ANN, and Neuro-Fuzzy are applied to facilitate flood prediction. The third chapter is introduced the study area and explain detailed methodology used for this study. In the fourth chapter, the findings of research are presented. The final chapter, conclusion, draws upon the entire thesis, gives a brief summary. It also includes an implication discussion of the findings for future research into this area. Detailed research data and results of ANN and Neuro-Fuzzy analysis and MATLAB programming are shown in the appendices. Schematic representation of the Thesis is shown in Figure 1.3.





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