The Integration of Geographic Information Systems and Capacitated Vehicle Routing Problem for Humanitarian Logistics: A Case Study of Preparedness for a Tsunami in Phuket, Thailand

By

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Abstract

This research is motivated by the lesson learnt from the 2004 Tsunami and the need to develop a post-tsunami aid delivery algorithm. To our knowledge, emergency planning for tsunamis in Thailand developed after the 2004 event that included only tsunami warning systems and evacuation procedures. However, there was no consideration of utilising an aid delivery algorithm, which critically depends on estimates of the affected population. With the use of geographic information systems (GIS), there has been renewed interest in spatial population estimation as well as map visualization. The main aim of this research, therefore, is to develop a decision support system (DSS) by integrating GIS and vehicle routing algorithm to facilitate decision-making for the purpose of being able to plan and operate humanitarian relief logistics efficiently and effectively.

To this end, this research encompasses three main development phases. Firstly, the algorithm of Affected Population Estimation (APE) is developed. A multi-stage spatial interpolation is proposed for estimating the affected populations using GIS functionalities in ArcGIS 10.3. A different perspective of a dasymetric-mapping technique using a population-weighted technique coupled with remote sensing data is presented in the first stage, while the street-weighted methods are addressed in the following stages. The results in each target zone include a range of numbers affected by the tsunami inundation.

Humanitarian Logistics Optimization (HLO) is the second phase of this research. In this phase, the Capacitated Vehicle Routing Problem (CVRP) with simulated demand is studied. The solutions generated from the population-estimation module are transferred to this phase in the form of estimated

demand, which has been assigned to each evacuation location. This study phase aims to solve the CVRP with simulated demand for humanitarian logistics. Being the combinatorial problem, the CVRP is modelled and solved by the Clarke and Wright Saving heuristic (CWS). Then, the quantities of demand are simulated using a Monte Carlo technique in order to obtain the most possible outcomes based on the seasonal-specific parameters. Together with the transport resource variables identified in the problem, the CVRP solutions include not only a set of routes with minimum cost but also transport resource efficiency and route priority. The transport resource ratio determines whether the given transport resources are sufficient for the operation deadline, while route priority is useful for decision-making in case the transport resources are limited.

In the last phase, the GIS-based DSS is developed based on the algorithms proposed in the first two phases. Hence, an application is programmed by combining those two algorithms, all of which are based on GIS utilization. The graphical user interface (GUI) is designed for very intuitive use, with the user only inputting a set of data and parameters. The main advantage of this GIS-based DSS is that the decision maker does not require special skills in GIS and in operating the complex processes in the ArcGIS environment. This innovative tool straightforwardly produces not only numerical solutions for the decision maker, but also visualisation maps on the GUI as well as in the ArcGIS system.

A case study of Phuket effectively illustrates the proposed DSS. The outcomes can be used as a key decision-making factor in planning and managing humanitarian relief logistics before and during the disaster response phase to improve their performance the next time around.

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Finally, I would like to show my gratitude to my family, especially my beautiful daughter, Pingrampha Jitt-Aer (Angie), and also my gorgeous son, Chanitnan Jitt-Aer (CJ). They are my true inspiration to achieve the PhD degree.

Wg.Cdr. Kiatkulchai Jitt-Aer

Declaration

Whilst registered as a candidate for the above degree, I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award.

Signature:

Table of Contents

Abstract i
Acknowledgement iii
Declaration iv
Table of Contents v
List of Tables viii
List of Figures x
List of Abbreviations xiii

Chapter 1: Introduction 1

1.1 Introduction 1
1.2 The 2004 Indian Ocean Tsunami 1
1.3 Occurrence and Impact of the 2004 Tsunami in Thailand 4
1.4 Problem Statement 6
1.5 Aims and Objectives 10
1.6 Thesis Outline 11
1.7 Chapter Summary 13

Chapter 2: Literature Review 14

2.1 Introduction 14
2.2 Humanitarian Logistics 14
2.3 Estimates of Population Affected by Disasters 16
2.3.1 Population estimation techniques 17
2.3.2 The importance of population estimation 18
2.3.3 Estimating population affected by disasters 20
2.4 Capacitated Vehicle Routing Problem and Solution Methods 23
2.4.1 The fundamentals of VRP 23
2.4.2 The CVRP formulation 25
2.4.3 The CVRP in practice and its extension 27
2.4.4 Solution methods for CVRP 29
2.5 Geographic Information Systems 32
2.5.1 The fundamentals of GIS 33
2.5.2 The applications of GIS 37
2.6 Chapter Summary 40

Chapter 3: Research Methodology 43

3.1 Introduction 43
3.2 Research Framework 43
3.3 Material Sources 47

3.3.1 Esri ArcGIS 10.3 software 47
3.3.2 Dataset and data collection 49
3.3.3 IntelliJ IDEA Community Edition 58
3.4 Methods 58
3.4.1 Data preparation 59
3.4.2 DSS development 64
3.5 Chapter Summary 72

Chapter 4: An Analysis of Pertinent Factors in the Case Study Area 73

4.1 Introduction 73
4.2 Geography of Phuket 74
4.3 Population of Phuket 78
4.4 The Impacts of the 2004 Tsunami in Phuket 80
4.4.1 Impact on human casualties 82
4.4.2 Impact on beachfront areas 83
4.4.3 Impact on transportation networks 84
4.4.4 Impact on water and electricity supply 85
4.4.5 Impact on tourism industry 85
4.4.6 Relief effort responded to the tsunami impact 86
4.5 Thailand Tsunami Master Plan 86
4.6 Chapter Summary 88

Chapter 5: A Method for Tsunami Affected Population Estimation 90

5.1 Introduction 90
5.2 Literature Review 92
5.3 Study Area and Dataset 97
5.4 Methodology 99
5.4.1 Areal interpolation techniques 101
5.4.2 GIS analytical operations 110
5.5 Experimental Results 113
5.5.1 A GIS-based application for estimating the affected 114
5.5.2 Experimental results 115
5.6 Chapter Summary 120

Chapter 6: The CVRP with Simulated Demand 122

6.1 Introduction 122
6.2 Literature Review 124
6.3 The CVRP Formulation 127
6.4 Study Area and Dataset 130
6.5 Methodology 133
6.5.1 Demand Simulation 134

6.5.2 The CWS heuristic for solving the CVRP 153
6.5.3 Additional solutions 157
6.6 Experimental Results 159
6.7 Chapter Summary 166

Chapter 7: The Integration of GIS and CVRP for DSS 168

7.1 Introduction 168
7.2 Literature Review 171
7.3 Study Area and Dataset 173
7.4 Methodology 175
7.5 Development of the GIS-based DSS 177
7.5.1 Affected population estimation (APE) module 178
7.5.2 Humanitarian logistics optimization (HLO) module 179
7.5.3 ArcGIS Network Analyst 181
7.6 Preparedness plan for humanitarian logistics 183
7.6.1 Proposed scenario on the APE module 183
7.6.2 Proposed scenario on the HLO module 188
7.7 Chapter Summary 206

Chapter 8: Conclusion 208

8.1 Conclusions and Recommendations 208
8.2 Research Contributions 211
8.3 Research Limitations 215
8.4 Suggestions for Future Research 216

Chapter 9: References 218

Appendix A 243

Appendix B 251

Appendix C 256

Appendix D 260

Appendix E 270

Appendix F 283

Appendix G 284

List of Tables

Table 1-1: The Asian tsunami, December 2004, casualties by country. 3
Table 1-2: Thailand tsunami, December 2004, casualties by province. 5
Table 3-1: GIS data sources. 51
Table 3-2: Document data sources. 52
Table 3-3: Tourist statistical data assigned to evacuation node. 64
Table 3-4: Control elements of the main GUI. 67
Table 3-5: Control elements of the APE user interface. 69
Table 3-6: Control elements of the HLO user interface. 71
Table 4-1: Phuket population (updated in 2016). 78
Table 4-2: Statistics of tourists visiting Phuket between 2009 and 2016. 80
Table 4-3: The number of affected people. 82
Table 4-4: The number of directly affected persons and households. 83
Table 4-5: Statistics of the hotels damaged by the 2004 tsunami. 86
Table 5-1: Numerical results for the threshold scenario. 115
Table 5-2: Parameter test in each flooding-scenario group. 116
Table 5-3: Numerical results of scenarios 1-3. 117
Table 5-4: Numerical results for scenarios 4-6. 118
Table 5-5: Numerical results of scenarios 7-9. 119
Table 6-1: Threshold scenario solution (extracted from chapter 5). 137
Table 6-2: Random number of decision parameters. 139
Table 6-3: Data of value Y and probability variable Z of the Z score. 147
Table 6-4: Problem scenarios based on decision parameters of demands. 151
Table 6-5: Proposed scenario for estimating affected population. 160
Table 6-6: Numerical results generated from the GIS-based application for estimating affected population. 160
Table 6-7: Threshold input variables for transportation resource management. 161
Table 6-8: Problem scenarios based on the seasonal parameters. 162
Table 6-9: Tourist statistical data assigned to evacuation node. 163
Table 7-1: Tsunami risk level. 185
Table 7-2: Risk level and tsunami surge height in each town of Phuket. 185
Table 7-3: Proposed problem scenario on the APES module for estimating affected population. 186
Table 7-4: Numerical results from the APE module. 187
Table 7-5: Problem scenarios based on seasonal parameters. 189
Table 7-6: The input variables for transportation resource management. 189
Table 7-7: The overall solution for the proposed scenario. 191
Table 7-8: Routing solutions for the proposed scenario. 191
Table 7-9: Demand served in each evacuation node in route 1. 193
Table 7-10: Demand served in each evacuation node in route 2. 194
Table 7-11: Demand served in each evacuation node in route 3. 195

Table 7-12: Demand served in each evacuation node in route 4. 196
Table 7-13: Demand served in each evacuation node in route 5. 197
Table 7-14: Demand served in each evacuation node in route 6. 198

List of Figures

Figure 1-1: The 2004 earthquake tectonic setting and seismicity map. 2
Figure 1-2: Strategic and local problems in the 2004 Thailand tsunami. 7
Figure 2-1: Classical vehicle routing problem. 24
Figure 2-2: Main components of a GIS 34
Figure 2-3: GIS functional elements. 35
Figure 2-4: Features comparison between freeware open source and commercial GIS software. 36
Figure 3-1: Logistics flow after a tsunami occurrence. 44
Figure 3-2: Integration structure. 45
Figure 3-3: Research framework. 46
Figure 3-4: The evaluation of street footprints. 50
Figure 3-5: DEM data of the study area. 53
Figure 3-6: Data of study area boundary. 54
Figure 3-7: Data of street network in the study area. 55
Figure 3-8: Vector map preparation. 59
Figure 3-9: DEM preparation. 60
Figure 3-10: Attribute database preparation. 61
Figure 3-11: Cost matrix preparation. 62
Figure 3-12: Evacuation node responsible to the nearest tourist spot. 63
Figure 3-13: DSS framework. 66
Figure 3-14: Main user interface design. 67
Figure 3-15: APE user interface design. 68
Figure 3-16: HLO user interface design. 70
Figure 4-1: Overall geography of Phuket. 75
Figure 4-2: Geographic condition along the west coast of Phuket. 76
Figure 4-3: Geographic condition along the east coast of Phuket. 76
Figure 4-4: Phuket attractions map. 77
Figure 4-5: Sub-districts in Phuket. 79
Figure 4-6: Patong area before and after the 2004 tsunami occurrence. 81
Figure 4-7: Tsunami impact on Patong Beach, Phuket. 84
Figure 4-8: Master plan for the tsunami evacuation. 87
Figure 5-1: Study area in Phuket, Thailand. 98
Figure 5-2: The overall process of estimating the affected population. 100
Figure 5-3: A comparison of the new perspective and traditional area-based interpolation. 104
Figure 5-4: Population-estimation evaluation using remote sensing imagery. 105
Figure 5-5: The GIS vector data for the street-weighted approach. 106
Figure 5-6: An example of estimating the population affected by tsunami flooding in an evacuation-node neighbourhood using the street-weighted interpolation technique. 108
Figure 5-7: Phases of the GIS analytical operations. 111

Figure 5-8: GUI and data and parameters input of the application. 114
Figure 6-1: The drawing of evacuation nodes across the tsunami-prone area. 131
Figure 6-2: Data structures. 132
Figure 6-3: Methodology for solving the CVRP. 133
Figure 6-4: The graph of discrete uniform distribution. 135
Figure 6-5: Generating a random demand X from a random variable u. 136
Figure 6-6: Trial results of randomised demand from uniform distribution. 138
Figure 6-7: Randomised demand using decision factor. 140
Figure 6-8: Numbers of tourists visiting Phuket between 2009 and 2016. 141
Figure 6-9: Change of scale to standard units. 143
Figure 6-10: Trial results of randomised demand from normal distribution. 144
Figure 6-11: Overall trend of tourists visiting Thailand between 2013 - 2016. 145
Figure 6-12: Control of random variable for peak and off-peak tourist season. 146
Figure 6-13: Trial results of randomised demand from normal distribution using decision parameter. 148
Figure 6-14: The overall process of modelling demand using MCS. 150
Figure 6-15: Simulation results of 1,000 iterations of each problem scenario. 152
Figure 6-16: Illustration of the savings concept. 153
Figure 6-17: The algorithm of the CWS. 155
Figure 6-18: The algorithm of creating initial routes. 156
Figure 6-19: The algorithm of creating resource efficiency and demand-cost efficiency in the solution. 158
Figure 6-20: Comparing the numbers affected between high and low travelling seasons. 164
Figure 7-1: Structure of the proposed DSS. 176
Figure 7-2: The main user interface of the DSS. 177
Figure 7-3: The user interface of the first DSS module: affected population estimation (APE). 178
Figure 7-4: The user interface of the second DSS module: humanitarian logistics optimization (HLO). 180
Figure 7-5: A routing solution imported in ArcGIS in the response phase. 182
Figure 7-6: Using Network Analyst functionality to avoid a damaged street and automatically find a new one to complete the delivery route. 182
Figure 7-7: Tsunami risk level in Phuket defined by DDPM, Thailand. 184
Figure 7-8: HLO framework. 188
Figure 7-9: Presentation of the scenario solution using parameter $t_l: r_1$. 190
Figure 7-10: The visualization of route 1 displayed on the DSS user interface. 193

Figure 7-11: The visualization of route 2 displayed on the DSS user interface. 194
Figure 7-12: The visualization of route 3 displayed on the DSS user interface. 195
Figure 7-13: The visualization of route 4 displayed on the DSS user interface. 196
Figure 7-14: The visualization of route 5 displayed on the DSS user interface. 197
Figure 7-15: The visualization of route 6 displayed on the DSS user interface. 198
Figure 7-16: Visualization map of route 1 using ArcGIS Network Analyst. 200
Figure 7-17: Visualization map of route 2 using ArcGIS Network Analyst. 201
Figure 7-18: Visualization map of route 3 using ArcGIS Network Analyst. 202
Figure 7-19: Visualization map of route 4 using ArcGIS Network Analyst. 203
Figure 7-20: Visualization map of route 5 using ArcGIS Network Analyst. 204
Figure 7-21: Visualization map of route 6 using ArcGIS Network Analyst. 205

List of Abbreviations

Abbreviation	Description
APE	Affected Population Estimation
CPU	CentralProcessing Unit
CVRP	Capacitated Vehicle Routing Problem
CWS	Clarke and Wright Saving
DART	Deep Ocean Assessment and Reporting of Tsunami System
DDPM	Department of Disaster Prevention and Mitigation
DEM	Digital Elevation Model
DOPA	Department of Provincial Administration
DOT	Department of Tourism
DSS	Decision Support System
EM-DAT	The Emergency Events Database
FOSS	Free and Open Source Software
GDB	Geographic Database
GIS	Geographic Information System
GRIMP	Global Rural-Urban Mapping Project
GUI	Graphic User Interface
HLO	Humanitarian Logistics Optimization
IFRC	Red Cross and Red Crescent Societies
IK	Indigenous Knowledge
MCS	Monte Carlo Simulation
NASA	National Aeronautics and Space Administration
OR	Operational Research
SRTM	Shuttle Radar Topography Mission
SVRP	Stochastic Vehicle Routing Problem
TSP	Travelling Salesman Problem
USGS	United States Geological Survey
VRP	Vehicle Routing Problem

Chapter 1: Introduction

1.1 Introduction

This dissertation is motivated by the lessons learnt from the 2004 Asian tsunami in the south of Thailand, which seriously stimulated both academics and practitioners to improve humanitarian relief logistics after the tsunami's onset. With this inspiration, this thesis begins with the background context and the problem statement which determines the particular aims and objectives for this research.

This chapter introduces the overarching themes of this dissertation and places the motivation for the work into context. Thereafter, the rationale and goals defined for the research are discussed. Then, an outline of the thesis is given on a per-chapter basis. Finally, the overall context presented in this chapter is summarised in the last section.

1.2 The 2004 Indian Ocean Tsunami

On December 26, 2004, a magnitude 9.3 earthquake with an undersea source in the Indian Ocean triggered a massive tsunami, one of the deadliest natural disasters ever. The epicentre of the quake was near the west coast of northern Sumatra. This earthquake occurred along a thrust fault in the subduction zone between the Indian and Burmese plates as shown in Figure 1-1. The Indian tectonic plate was forced under the Burmese plate, making the plates overlap and disrupting the seabed. As a result, there was a vertical movement along the fault, causing a large-scale displacement of water and generating tsunami waves.

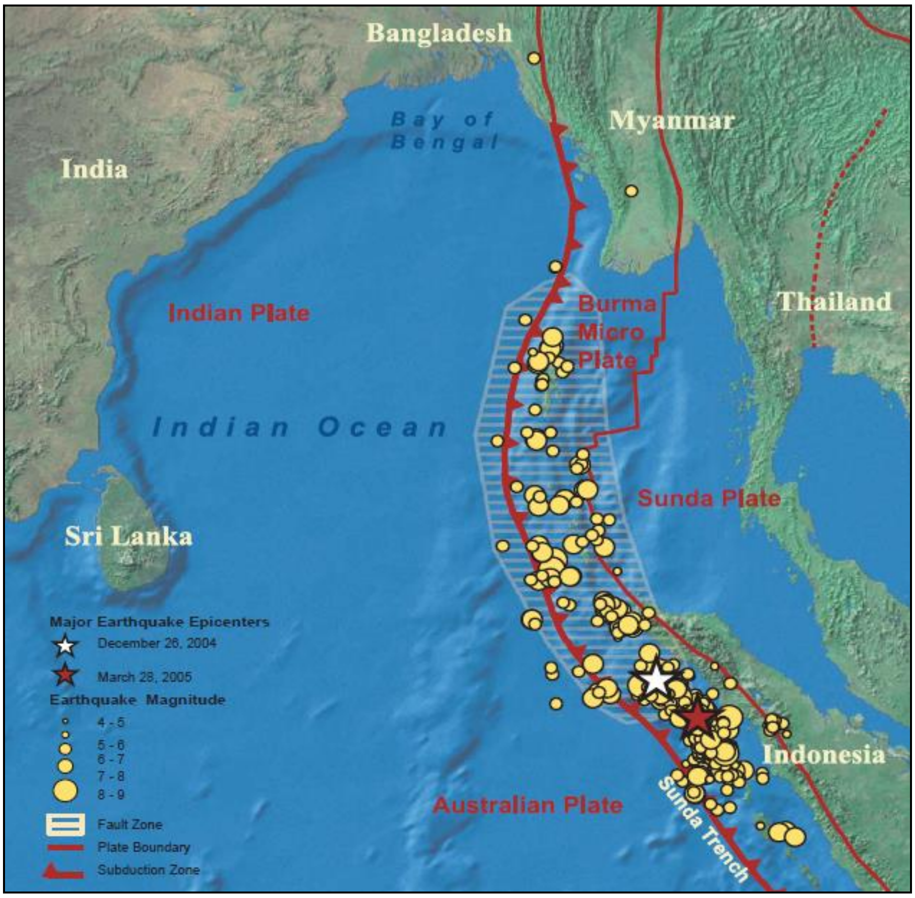


Figure 1-1: The 2004 earthquake tectonic setting and seismicity map.

Source: Fehr *et al*., 2014

Tsunami waves up to 30 metres moved to the shores of the Indian Ocean, hitting Indonesia, Sumatra, Sri Lanka, southern India, Thailand, and other coastal countries. The event caused 184,167 deaths, with 51,500 people missing and roughly 1.5 million people displaced. Moreover, many non-residents travelling in the region also were reported dead or missing. The toll of human casualties from the 2004 tsunami has no modern historical equal; Table 1-1 shows the casualties by country.

Country	**Death**		**Injured**
	Confirmed	**Estimated**	
Indonesia	130,736	167,736	N/A
Sri Lanka	35,322	35,322	21,411
India	12,405	18,045	N/A
Thailand	5,395	8,212	8,457
Somalia	78	289	N/A
Myanmar	61	400-600	45
Maldives	82	108	N/A
Malaysia	68	75	299
Tanzania	10	13	N/A
Seychelles	3	3	57
Bangladesh	2	2	N/A
South Africa	2	2	N/A
Yemen	2	2	N/A
Kenya	1	1	2
Total	**184,167**	**230,210**	**125,000**

Table 1-1: The Asian tsunami, December 2004, casualties by country.

Source: Tatham and Christopher, 2014

In addition to the casualties, it shows the tsunami ruined communities at sea level. The powerful waves had an extreme impact on the affected countries, washing away their inhabitants and infrastructure and causing massive pollution and destruction of fresh water supplies.

In the aftermath of the disaster, the people were faced with a lack of supplies to meet basic needs combined with inefficient relief logistics faced by international, national and local humanitarian organizations. Moreover, in most affected countries, humanitarians failed to get supplies to affected populations in the early stage of the response phase due to chaos in the affected areas and a lack of response mechanisms for this large-scale tsunami.

1.3 Occurrence and Impact of the 2004 Tsunami in Thailand

The tsunami stimulated from the Indonesia earthquake hit the south west coast of Thailand. This seismic sea wave travelled thousands of kilometres across the Indian Ocean and ravaged the Andaman coast of southern Thailand at 9:30 am local time. Coastal provinces affected included Phuket, Phang-Nga, Krabi, Ranong, Trang and Satun. In the affected area, the tsunami destroyed infrastructure and social services, villages and livelihoods on a scale never before seen in Thailand. The most devastated areas in terms of loss of life were in Phang-Nga, Krabi and Phuket, not just because of their location, but because they were the most developed and most densely populated areas along the coast.

The tsunami hit Thailand at Kata and Patong beach in Phuket first. Less than 10 minutes later, it struck the Khao-Lak area, a renowned tourist site. The height of the waves at Khao-Lak were even higher than at Phuket; up to 10 meters. Within half an hour of the strike, areas were flooded and subsequently covered by mud and debris. The force of the waves destroyed everything in their path. The tsunami inundation in Thailand caused at least 5,395 deaths, more than 8,000 injuries and more than 2,500 people missing, classified by province in Table 1-2. Remarkably, of those who died in Thailand, almost half were vacationing foreigners. This tsunami was the worst natural disaster in Thailand’s written history.

Tatham and Christopher (2014) reported that specific impacts of the tsunami encompassed communication system failures due to the destruction of the telecommunication network, mass structural damage, large volumes of accumulated debris and extensive flooding. These impacts resulted in the difficulty of operating humanitarian logistics. Also, before 2004, Thai authorities believed that a tsunami would never occur, and thus there was no plan for dealing with relief operations in the aftermath of a tsunami.

Province	Death	Injured	Missing
Phang-Nhga	4,224	5,597	1,733
Krabi	721	1,376	569
Phuket	279	1,111	620
Ranong	160	246	9
Trang	5	112	1
Satun	6	15	0
Total	**5,395**	**8,457**	**2,932**

Table 1-2: Thailand tsunami, December 2004, casualties by province.

Source: Ministry of Interior, Thailand

As a direct consequence of this event, Thai authorities increasingly have paid attention to disaster prevention, contingency planning and emergency relief operations to be able to better respond to emergencies such as a tsunami. Some essential structures have been developed for tsunami prevention and mitigation. Firstly, on a macro level, the Pacific Ocean Tsunami Warning System was established in 2005 to watch for an occurrence of a tsunami. Secondly, on a national level, Thailand installed facilities essential for a tsunami response (e.g. tsunami warning towers, information dissemination system, signposting) with the hope that these developments would help improve response mechanisms. The emphasis on reference to the distribution of aid materials also has been mentioned, but the details of transport and logistics support have not been directly and clearly stated.

In Thailand, it is reasonable to develop mechanisms for coping with tsunamis as it is likely that earthquakes and subsequent tsunamis will occur in the same region in the future, although it is more difficult to predict when because Thailand is located close to the Indian Ocean subduction zone where the Indian and Burmese tectonic plates are still moving at a regular rate over time. This can cause significant movement of the seabed in the future and result in tsunamis.

As can be seen from the evidence of the 2004 regional and 2005 local tsunamis (see Figure 1-1), the Indian Ocean coastal countries, which include Thailand, are characteristically vulnerable for earthquakes and subsequent tsunamis. Therefore, it is essential that both academics and practitioners study tsunami preparedness and response mechanisms in Thailand to cope with a future tsunami. The lessons learned from the tragic event in 2004 may be good guidance for those who are interested in developing innovations for tsunami prevention and mitigation. When a tsunami occurs, the mechanism of humanitarian logistics is one of the most vital aspects to be developed for timely fulfilling of basic needs for people affected by the tsunami.

1.4 Problem Statement

To identify potential problems, a number of issues reported by the Ministry of Interior, Thailand, in the 2004 tsunami (see Figure 1-2) should be considered. Another interesting aspect is that the Thai government developed a Master Plan for Tsunami Evacuation, trying to eliminate the shortcomings reported from the 2004 event. The Master Plan highlights communications infrastructure, evacuation procedures, victim support and distribution of relief supplies.

During the 2004 tsunami, neither quick data analysis nor on-the-ground warning systems were in place. Since then, however, the Thai government has worked to remedy those inadequacies by installing a tsunami evacuation system with alarm towers along the coasts in the tsunami-prone areas, as well as communication mediums and clearly marked evacuation routes in densely populated areas. This development was unexpectedly tested in April 2012 after an earthquake in the same region triggered a tsunami warning. In this situation, however, no tsunami followed the quake. Evacuees finally received a signal to return to their property.

After the tsunami in 2004 and the tsunami warning in 2012, the Thai government started gathering essential equipment in terms of life saving, communications and data handling for coping with future tsunamis. This would remedy most problems at both the strategic and local levels as stated in Figure 1-2.

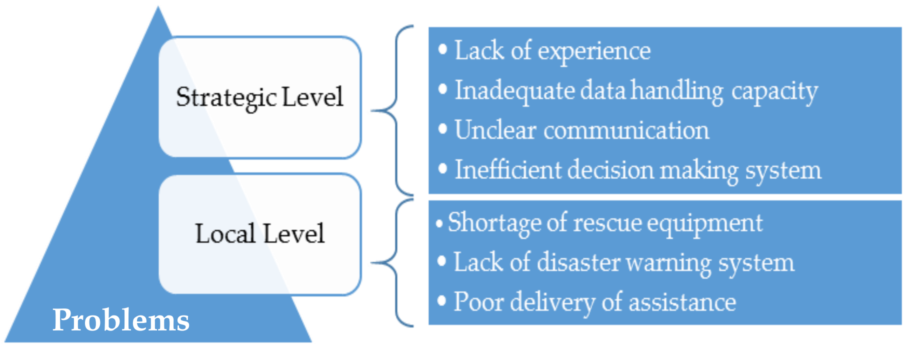


Figure 1-2: Strategic and local problems in the 2004 Thailand tsunami.

Regarding humanitarian assistance, the Master Plan for Tsunami Evacuation also underlines the response aspect. As a result, safe places for tsunami evacuation have been established and are the responsibility of each regional relief supply centre in the tsunami-prone areas. For example, the relief supply centre in Phuket is responsible for 38 evacuation nodes dispersed throughout the area. Each location is defined as a safe place in case of tsunami inundation, meaning they are either outside the zone affected by the 2004 tsunami or are on land more than 15 metres above sea-level.

In terms of supply preparedness, each regional relief centre has established a long-term collaboration with its suppliers for aid materials by making a sale-and-purchase agreement in case aid is needed immediately for relief operations.

Nevertheless, it seems that there is little specific reference in the Master Plan regarding a mechanism of delivering relief supplies to a displaced population. The regional relief centres in the tsunami-prone areas are not given explicit transport strategies for serving the basic needs of evacuees and casualties on a timely basis. This aspect must receive greater concern because, as Tatham and Christopher (2014) mentioned, after the 2004 tsunami waves hit the coast of Thailand, a wide range of problems arose in the delivery of assistance to the victims. This was because the tsunami destroyed properties, infrastructure and social services in its path, and the affected people then experienced a lack of food, water and basic medical care. Delivering such essential needs inefficiently could result in a worse situation due to malnutrition and illnesses. Thus, this issue should receive more attention among humanitarians as it is not only a matter of cost but also of life and death.

Developing an efficient logistics mechanism in the disaster context may not be easy. When a tsunami occurs, efficient humanitarian logistics depends critically on an estimation of the affected population. As natural disasters rarely respect the administrative or political boundaries for which official population data are collected, retrieval of these records may not be the best option accounting for the population affected by the tsunami. Thus, not knowing the affected numbers can hinder the logistics operation, making the allocation of relief supplies inefficient and ineffective.

In addition, population distributions basically are based on the spatial nature of an area; thus, acquiring a population estimation usually comes with the challenge of spatial population distributions. Moreover, non-residents may need to be considered especially in Thailand’s tsunami affected area, which is a tourist spot. Hence, considering non-residents can contribute to a more accurate estimation of the population affected by a tsunami.

Of the aforementioned difficulties, poor population estimation in the affected area is a critical impediment to distributing aid efficiently and effectively. A method of population estimation in the disaster context, therefore, must be considered to achieve efficient humanitarian logistics.

Furthermore, transporting items to alleviate suffering at the right time with the right demand can be very difficult in the real-word humanitarian logistics. A tsunami usually impacts several locations with many evacuation nodes in which people are waiting for help. Thus, modelling a distribution of supplies from a relief centre to numerous evacuation locations can be mathematically complicated. In addition to the complexity of distribution models, real-life deliveries in disaster relief usually encounter the spatial nature that is not considered by such models. Therefore, managing relief deliveries to many locations is also a major problem regarding the intricacy of both mathematical and terrestrial issues.

In the respect of decision-making technology for facilitating aid deliveries in a tsunami incident, developing a decision-making system for relief logistics has received little attention so far in Thailand although this aspect was stated as one of the strategic-level problems after the 2004 tsunami (see Figure 1-2). Consequently, efficient innovative platforms are required for dealing with a complex distribution system in the aftermath of a tsunami.

In summary, according to the lessons learned from the 2004 tsunami, Thailand highlighted the major problems at both a strategic and local level, inspiring the government to establish the Master Plan for Tsunami Evacuation to eliminate those inadequacies and to improve disaster prevention and mitigation for future tsunami events. According to existing development, however, there is still an essential need to develop a decision-making system, an aid-delivery algorithm and technology to ensure the humanitarian logistics can be efficiently planned and operated so that people affected by the tsunami receive relief deliveries effectively.

1.5 Aims and Objectives

The aim of this research is to develop a decision support system (DSS) for humanitarian logistics. The DSS is performed by integrating geographic information systems (GIS) and algorithms and methods that couple a heuristic approach and techniques from probabilistic analysis to solve the capacitated vehicle routing problem (CVRP) with simulated demand, which heavily depends on affected numbers. The overall purpose of the GIS-based DSS is to support decision makings for efficient aid-delivery operations in the case of a tsunami striking Thailand.

To achieve the research aim, some specific objectives are considered:

- ❖ Design and develop a spatial algorithm to estimate the population affected by a tsunami inundation
- ❖ Develop and implement an application by combining GIS and the population estimation method
- ❖ Implement a CVRP model and its solution method for aid delivery in the aftermath of a tsunami
- ❖ Develop and implement a DSS for post-tsunami aid delivery by integrating GIS and CVRP optimization for humanitarian logistics

These objectives can be achieved by:

- Reviewing the literature on natural disasters, humanitarian logistics, spatial population estimation, the vehicle routing problem and its solution methods, and GIS technology.
- Developing a strategy of using areal interpolation methods to estimate the population affected by a tsunami.
- Developing a GIS-based application to estimate the affected population in the study area.
- Formulating a CVRP model and implementing Clarke and Wright Saving (CWS) heuristics for solving the model.
- Applying the Monte Carlo technique to simulate demand to input into the CVRP model.
- Developing a GIS-based platform for visualising the CVRP optimization results.
- Integrating the GIS-based application for estimating affected population and the GIS-based platform for the CVRP to form the proposed DSS.

1.6 Thesis Outline

This thesis expresses the concept of developing a DSS to facilitate decision making regarding humanitarian logistics in the case of a tsunami affecting Thailand area. The integration of GIS and CVRP optimization is the backbone of DSS in this research. This innovative system provides both numerical and geographical solutions for decision makers to plan and manage aid deliveries before and during the disaster response phase. This thesis is structured into eight chapters as follows:

Chapter 1 introduces the subject area of the research, including the occurrence of the 2004 Asian tsunami and its impacts on Thailand as the motivation, the problem statement, aim and objectives, and the structure of the thesis.

Chapter 2 provides a review of the literature of natural disasters, humanitarian logistics, spatial population estimation, the VRP and its solution methods, and GIS technology. This chapter also includes a discussion of the related subjects and describes the relationship of previous works while identifying the most significant literature that contributes to this research.

Chapter 3 explains the characteristics of the study area in terms of geography, administrative division, demography and the consequences in the area caused by the 2004 tsunami.

Chapter 4 elucidates the research conceptual frameworks. This chapter also provides a description of the sources and acquisition of data, and the research methodology.

Chapter 5 presents the method of estimating the affected population in the study area, reviews interpolation methods and discusses previous work across disciplines. Moreover, this chapter explains the areal interpolation techniques used to estimate the population in the study area and tests case study scenarios to find a set of numerical solutions, which is followed by a discussion.

Chapter 6 proposes a CVRP formulation for use in the disaster relief context. This chapter also explains the CWS algorithm used to solve the VRP model. Also, the solution results using the instance from the study area are experimentally produced.

Chapter 7 proposes a DSS for humanitarian logistics using the case study. Also, this chapter reviews related subjects and previous works and presents a test of the method of solving the VRP with simulated demand through use of a set of instances from the study area. Specifically, the CWS algorithm is used to solve the VRP optimization. Furthermore, the methodology of developing the system is explained with an experiment of case scenarios. The numerical results are transformed to the visualization map. Finally, the routing solutions also are produced in the ArcGIS platform so the decision maker can gain more specific details with the ability to adjust the results based on updates to the current impact.

Chapter 8 provides conclusions of the research with recommendations. It also includes research contributions, and suggestions for future research.

According to the chapter outline, it is worth noting that Chapter 2 provides a general review in order to understand the research area in a broad context. However, more in-depth reviews are included in the following chapters; Chapter 5, Chapter 6, and Chapter 7, to specify the research context into a particular area in accordance with the content of each chapter.

1.7 Chapter Summary

This chapter shows the overall picture of the research by introducing background and information motivated by the response to the 2004 tsunami and its impacts in Thailand. The discussion of the problem statement based on the issues reported from the lessons learned from the 2004 event and the following Master Plan for Tsunami Evacuation reveals potential problems that, in turn, results in the proposed research aim and objectives. The last part of the chapter explains the thesis structure and illustrates a summary of each chapter in this thesis.

Chapter 2: Literature Review

2.1 Introduction

This chapter reviews, describes and discusses the relevant subjects that are considered as a stepping stone to the goal of this research. The investigation serves five purposes. Firstly, natural disasters are basically described in the Appendix A. Next, tsunami characteristics and tsunami hazard assessment are fundamentally illustrated in the Appendix B. Then, in this chapther, the basic concept of humanitarian logistics is proposed in section 2.2. Subsequently, estimates of population are conceptually explained and also discussed within the existing studies on the disaster context in section 2.3. The latter, section 2.4, elucidates the Capacitated Vehicle Routing Problem and its extension in the practical areas; furthermore, its solution methods are investigated in order to use for solving such combinatorial optimization problems. Following, section 2.5 explains the fundamentals of the Geographic Information System, and investigates its current uses in practice. Finally, section 2.6 summarises the chapter.

2.2 Humanitarian Logistics

In recent years, the humanitarian logistics has attracted the attention of researchers due to the increasing frequency of disasters (the foundation of humanitarian logistics are elucidated in the Appendix C). Also, the nature of disasters with uncertain factors (e.g. time, location, severity) can make humanitarian logistics operations difficult to handle. An efficient manner for operations, however, can reduce human and economic losses. Therefore, it is meaningful to highlight this subject as a potential research area.

To maximize performance, it is imperative to understand the features of humanitarian logistics, perhaps by comparing it to commercial logistics. Humanitarian and commercial logistics have been mentioned distinctively in the literature. For instance, the management of limited resources and infrastructure, as well as the collaboration of multiple organizations, are more critical in humanitarian logistics than in commercial logistics (Ergun *et al.*, 2009).

Humanitarian aid operations need to be lean and agile to rapidly alleviate the suffering of people (Tatham and Christopher, 2014). Thus, the speed of response in humanitarian logistics is more important than in commercial logistics. This is consistent with Cozzolino (2012), who found the effectiveness of humanitarian logistics is about ensuring the saving of time, and time saved means more lives saved.

Moreover, Lee *et al*. (2009) suggest that there are a number of factors that make humanitarian logistics unique, such as a massive flow of demand. With respect to demand, demand for goods is variable and difficult to forecast in humanitarian logistics (Van Wassenhove, 2006). This also corresponds to the supply side as the commodities handled in a disaster relief operation are usually much more varied than those handled by the business sector (Long, 1997). Therefore, inefficient management of supply in disaster relief can occur more easily.

In contrast to humanitarian logistics, the nature of commercial logistics operations is most likely to be operating the same routine within a supply chain (Holguín-Veras *et al.*, 2012; Long, 1997). For example, the nature and destination of cargo usually are known; therefore, it is not difficult to optimize the delivery tasks. Furthermore, commercial logistics normally deals with a predetermined set of organizations and a stable predictable demand (Kovács and Spens, 2007). Thus, it is likely that business logistics is not as uncertain and complex as humanitarian logistics. For example, as suppliers make deliveries to customers on a routine basis, acquisition of customer demand can be easier because future demands can be forecast based on historical data. On the contrary, in the disaster aspect, both location and customers (casualties in this case) are unknown in advance.

When a disaster occurs, uncertain factors can make humanitarian logistics inefficient and ineffective, and especially unknown demand can result in misdirected aid deliveries for people suffering from the disaster. Thus, quick retrieval of demands, which critically depends on an estimation of the affected population, is the most important contributor for successful humanitarian logistics. The next section focuses on the review of estimating population affected by a disaster.

2.3 Estimates of Population Affected by Disasters

Population estimation plays a vital role in disciplines such as social, political, economical and environmental studies (Liu, 2003). Estimates of population are popularly applied in the public and private sectors, especially estimating population in small areas or subareas. Because of population size and data availability issues, population estimation in small areas face some methodological challenges not commonly encountered in larger geographical scales (Rayer, 2015).

Particularly in a disaster situation, estimating the affected population for small areas is more challenging as the disaster rarely respects the geographical boundaries of the areas affected. Thus, this section attempts to explain, review and discuss the methodology of population estimation, the importance of estimating population, the challenges of this approach in the disaster context and potential solutions.

2.3.1 Population estimation techniques

In population estimation, people applying demographics consider the information about a past or present population based on a census or population register being an estimate (Rayer, 2015). In the scales of state and nation, a population estimation basically is a calculation of the size of a population for a year between census periods. Population estimation in a small area commonly involves administrative units including cities, municipalities, local government areas, census tracts and census blocks. Alternatively, a small area can refer to any subpopulation for which direct estimates of adequate precision cannot be produced (Rao and Molina, 2015).

When census data cannot provide an accurate and timely snapshot, administrative records may provide data on the number of households in a given region (ACAPS, 2012). In combination with other estimates of household size, this information can be used to generate total population estimates for subnational areas. For example, community health, water and food consumption, education and electricity statistics all can indicate the overall size of the population. Moreover, population counts can be inferred by population-relevant variables such as land use, building, street networks and city light (Wu *et al.*, 2008). In addition, to estimate the population figure in an area, demographic data can be combined with such variables to generate a feasible image of how populations are spatially distributed (Chen, 2002).

Interestingly, census unit populations can be disaggregated into homogeneous zones delineated by spatial variables that are related to the population distribution. This approach can be referred to as the dasymatric-mapping method (Robinson *et al.*, 1995). The most commonly used variables for census population disaggregation are land use and land cover data (e.g. Yuan *et al.*, 1997; Mennis, 2003; Holt *et al.*, 2004). Other variables that have been used include road networks (e.g. Hawley and Harold, 2005; Reibel and Bufalino, 2005), remote sensing image spectral and textural statistics (e.g. Liu *et al.*, 2006; Wu *et al.*, 2006) and other relevant physical or socio-economic variables (e.g. Dobson *et al.*, 2000; Liu and Clarke, 2002).

To disaggregate a census unit population based on relevant variables, researchers must establish a mathematical relationship between population counts and other variables. For example, when disaggregating a census population based on land use variables, researchers must determine the population density for each land use class or the population density ratio between land use classes before redistributing the census unit population to different land use zones. The mathematical relationship between population counts and relevant variables can be established by sampling (e.g. Mennis, 2003), from regression analysis (e.g. Wu *et al.*, 2006) or based on the knowledge of researchers (e.g. Eicher and Brewer, 2001).

2.3.2 The importance of population estimation

Population estimation is a commonly used characterization of geographic space at a wide range of scales. Estimates of population are useful in hazard planning and response, environmental impact assessment, transportation planning, economic decision-making and numerous other applications. Useful estimates of population must be made at appropriate, application-specific, spatial and temporal scales. As seen in the literature, population estimation is a vital method that can be widely applied in two characterizations: common and emergency situations.

In the common state, the size and distribution of a population serve as key determinants of resource allocation for state and local government (Smith *et al*., 2002). In particular, population estimates are critical in decisions of when and where to build public facilities such as schools, hospitals and transportation infrastructure.

In addition to public facility planning, the private sector often uses population estimates for customer analysis, market area delineation and site location identification (Martin and Williams, 1992). Moreover, population information is also an important input in many urban and regional models, such as land use and transportation interaction models, urban sprawl analysis, environment studies and policy impact analysis (Rees *et al*., 2004).

In addition to the common environment, population estimation also plays a vital role in most types of emergencies. Most crises disrupt communities, and many displace people. The size and demographic characteristics of the affected population may change because of displacement, migration or destruction of infrastructure. Timely, accurate and reliable information of people affected by a disaster is crucial for effective and efficient humanitarian response (WFP, 2007).

Estimates of affected population numbers are needed throughout the various phases of a disaster. A government census or recent survey provides the number and characteristics of people in the affected area before the disaster, enabling responders to derive the number of people in need of assistance. Estimating the affected population can be significantly inaccurate, however, when implementing this process in a catastrophe event due to a number of uncertain factors.

2.3.3 Estimating population affected by disasters

Over the past several decades, natural disasters have become more frequent across the world, and the populations affected by disasters have been increasing every year. Thus, the small-area population estimation applied in the public domain also can be used in the humanitarian sector.

Furthermore, nowadays more people have come to settle their property in zones of hazardous terrain (Teeuw, 2007) such as coastal areas, perhaps due to business reasons. They then are placing themselves as a population at risk from natural disasters like flood and tsunami. Therefore, making a population estimate is an urgent need in the disaster context. However, several challenges of estimating population affected by disasters have been described by ACAPS (2012):

- Disasters seldom occur within an entire administrative boundary, so area-based population figures may provide an incomplete picture.
- Disasters sometimes affect a specific population group or “hard-to-reach population” such as nomads or pastoralists, for which reliable or current population data is sometimes difficult to access.

- Disasters often involve population movements that can be temporary, permanent or back-and-forth; consequently pre-existing demographic data does not represent the current situation.

Since most population estimation approaches rely on census or administrative records, more challenging aspects are identified. For example, official demographic data tend to be weak, outdated and statistically representative only at relatively high levels of administrative aggregation in many developing countries (Nordhaus, 2006). When the census is outdated, demographic information often is not reliable and precise (Henderson, 2006).

Furthermore, official population data may not be applicable for emergency purposes like population assessment for disaster impacts. This is because in many countries the census population figures actually are based on people's home address rather than where they are physically present during the day (Wu *et al*., 2005). For example, Phuket has a much higher daytime population than that reported by the census because of its high proportion of tourists. Ignoring this important factor would make population estimation in an emergency situation inaccurate. When information is unreliable or incorrect, the humanitarian response may be insufficient, misdirected or delayed. Therefore, the generation of accurate and timely population estimates in the disaster context is crucial.

There have been some promising techniques proposed in the literature to deal with the challenges for estimating population affected by disasters. For example, the US National Research Council, (2007) suggests some potential approaches that would be helpful for an estimation:

- Test the accuracy of estimates of population size and distribution based on remotely sensed imagery, especially in rural and urban areas of countries with spatially, demographically and temporally inadequate census data.

- Improve analyses of vulnerability to natural disasters to define hazard areas where routine, periodic data collection could occur.

As mentioned in the US National Research Council's (2007) suggestion, another interesting perspective for estimating the affected population is the approach of assessing hazard areas. This is because the quantitative expression of the size of the population affected by a disaster is a central part of the hazard assessment process. After defining the geographical area affected by a disaster, it will be possible to estimate the affected population in need of the humanitarian response and to set priorities of relief plans and programmes. This is consistent with Kaiser *et al.* (2003), who stated the location and number of people affected by a natural disaster serve as a basic measure of the scope and magnitude of the response. Moreover, if possible, an assessment in terms of both affected areas and subsequent population at risk should be made before a disaster occurs to obtain an overall idea of disaster prevention and mitigation.

Developing hazard assessment and subsequent vulnerability analyses could help provide accountability to decision makers in preparedness and response. Particularly in the population aspect, when the affected population is estimated, a level of demands usually can be interpreted based on the affected numbers. This will facilitate decisions to be made for optimizing delivery routing in the last-mile distribution for alleviating the suffering of those affected. Therefore, routing optimization is reviewed in the next section.

2.4 Capacitated Vehicle Routing Problem and Solution Methods

Restricted transportation resources, high planning intricacy and the pressure of increasing cost make it essential to use mechanisms for the planning of transports. An important subtask in this context is the operational planning of vehicles. This optimisation task is called Vehicle Routing Problem (VRP). This section describes the basic concept of VRP, its mathematical formulation, its extension for the practical uses, and the solution methods commonly used for solving the problem.

2.4.1 The fundamentals of VRP

Initially, the classical Vehicle Routing Problem (VRP) objective was to design the least cost routes for a vehicle fleet to supply goods from inventory to customer demand locations. The problem was first introduced by Dantzig and Ramser (1959) to solving a real-world application concerning the delivery of gasoline to a set of service stations. The general concept of the VRP was simply stated by Rand (2009, p.125) as "a set of customers with known location and demand are to be supplied from a depot by delivery vehicles of known capacity subject to all customer demand being met, vehicle capacity not being exceeded and total trip length not exceeding some specified level". Figure 2-1 illustrates a simple VRP model presented by Bodin *et al.* (1983). Almost all the VRP models and algorithms are for normal operations that minimise cost, represented by travel distances or travel times and applied in operating logistic systems.

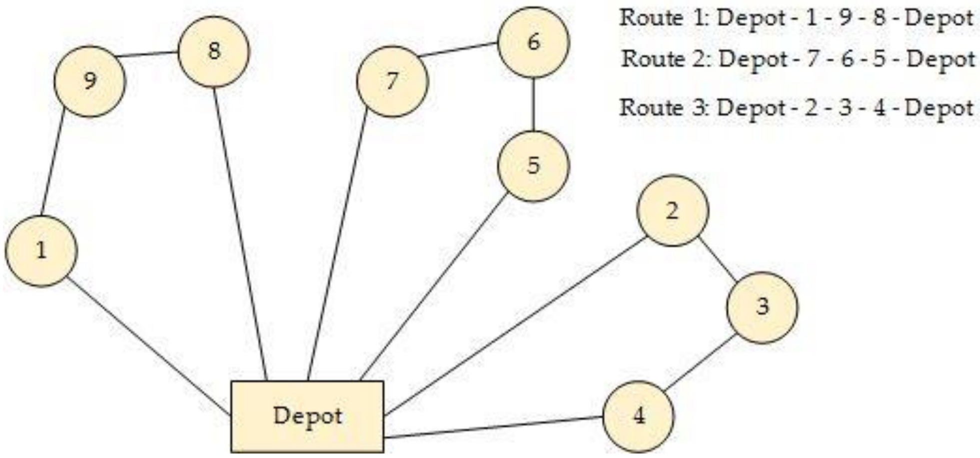


Figure 2-1: Classical vehicle routing problem.

Source: Bodin *et al.*, 1983

The VRP is a well know problem, which has been tackled by researchers for several decades. It is not only because of its potential applications but also because it can be used to test the efficiency of new algorithms and optimisation methods. The classical VRP is known as NP-hard as it is a generalisation of the Travelling Salesman Problem (TSP), which in itself is NP-hard (Garey and Johnson, 1979).

The standard version of the VRP is the Capacitated Vehicle Routing Problem (CVRP) (Chen *et al.*, 2010; Szeto *et al.*, 2011; Marinakis *et al.*, 2013). According to Juan *et al.* (2010), in the CVRP a set of customer demands has to be served with a fleet of vehicles from a depot. Each vehicle has the same limited capacity and each customer has a certain demand that must be satisfied and is known beforehand. Additionally, there is a cost matrix that measures the costs associated with moving the vehicle from one node to another. These costs usually represent distances or travelling times.

The objective of CVRP is to determine an optimal route schedule which minimises the cost with the following constraints (Kanthavel and Prasad, 2011);

- Each customer is served exactly once by one vehicle
- Each vehicle starts and ends its route at the same depot
- The total length of each route must not exceed the constraint
- The total demand of any route must not exceed the capacity of the vehicle

2.4.2 The CVRP formulation

The CVRP mathematical model was fundamentally formulated by Bodin *et al.* (1983) to explain the objective function and its constraints. The objective function is expressed in equation (1), which aims to design a set of routes that minimises the total distance covered by the entire fleet. The customer is visited only once by a vehicle and this is ensured by the equations (2) and (3), where the vehicle visiting between two customers is assigned as $x_{ij}^{k} = 1$ otherwise 0 to obtain the objective function. The vehicle tour starts at the depot, visit customers in sequence and finish at the same depot. In this tour, the vehicle needs to visit the customers continuously, i.e. if the vehicle enters a demand node, it must exit from that node; thus, equation (4) ensures the route continuity of the vehicle. Equation (5) represents the vehicle capacity constraints; similarly, equation (6) expresses the total elapsed route time constraints. Finally, equations (7) and (8) guarantee that vehicle availability is not exceeded.

$$\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{v=1}^{NV} c_{ij}x_{ij}^{v} \tag{1}$$

Subject to

$$\sum_{i=1}^{n}\sum_{v=1}^{NV} x_{ij}^{v} = 1 \qquad (j = 2, \dots, n) \tag{2}$$

$$\sum_{j=1}^{n}\sum_{v=1}^{NV} x_{ij}^{v} = 1 \qquad (i = 2, \dots, n) \tag{3}$$

$$\sum_{i=1}^{n} x_{ip}^{v} - \sum_{j=1}^{n} x_{pj} = 0 \qquad (v = 1, \dots, NV; p = 1, \dots, n) \tag{4}$$

$$\sum_{i=1}^{n} d_i \left(\sum_{j=1}^{n} x_{ij}^{v} \right) \leq K_v \qquad (v = 1, \dots, NV) \tag{5}$$

$$\sum_{i=1}^{n} t_i^{v} \sum_{j=1}^{n} x_{ij}^{v} + \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}^{v} x_{ij}^{v} \leq T_v \qquad (v = 1, \dots, NV) \tag{6}$$

$$\sum_{j=2}^{n} x_{1j}^{v} \leq 1 \qquad (v = 1, \dots, NV) \tag{7}$$

$$\sum_{i=2}^{n} x_{1i}^{v} \leq 1 \qquad (v = 1, \dots, NV) \tag{8}$$

Where n = number of nodes; NV = number of vehicles; K_v = capacity of vehicle v; T_v = maximum time allowed for the route of a vehicle v; d_i = demand at node i (d_1 = 0); t_i^v = time required for vehicle v to deliver or collect at node i

(t_1^v = 0); t_{ij}^v = travel time for vehicle v from node i to node j ($t_{ij}^v = \infty$); c_{ij} = cost of travel from node i to node j; x_{ij}^v = 1 if arc $i - j$ is traversed by vehicle v, 0 otherwise.

2.4.3 The CVRP in practice and its extension

The CVRP plays a vital role in distribution and logistics. In real time logistics, transportation is the key operation with model building and developing solution techniques for CVRP being the basic steps to solve complex models. In the business sector, CVRP is formulated to determine the optimal set of routes to be performed by a fleet of vehicles to serve a given set of customers. In practice, the CVRP is usually extended with constraints, for instance, on the allowed capacity of the vehicle, length of route, arrival, departure and service time, time of collection and delivery of goods. As a result, a variety of VRP variations have been studied in the literature. The extended classes of VRP are VRP with time windows, VRP with pick-up and delivery, Time dependent VRP, Dynamic VRP, Period VRP, VRP with backhauls, Open VRP, and Stochastic VRP.

In the VRP literature, there has been significant research on either the classical VRP version (e.g. Eksioglu *et al*, 2009; Laporte, 1992; Liong *et al.*, 2008) or its different variants: the capacitated VRP (e.g. Baldacci *et al.*, 2010; Toth and Vigo, 2014), VRP with time windows (VRPTW), pick up and deliveries and periodic VRP (e.g. Solomon and Desrosiers, 1988), dynamic VRP (DVRP) (e.g. Psaraftis, 1995), periodic VRP (PVRP) (e.g. Mourgaya and Vanderbeck, 2006), Split Deliver VRP (SDVRP) (e.g. Archetti and Speranza, 2008). However, all of these methods only consider deterministic VRP, which normally contain static elements of the problem. The classical VRP model usually does not capture the important aspect of real life transportation and distribution-logistic problems. This is due to the fact that several of the problem parameters such as demand, time and distance, and others are stochastic by their nature, but they are often oversimplified and treated as deterministic (Ak and Erera, 2007). Therefore, Stochastic Vehicle Routing Problem (SVRP) is an extension of the deterministic VRP in which some components are randomised. The three most common cases are:

- Stochastic customers: customer i is present with probability p_i and absent with probability $1-p_i$;
- Stochastic demands: the demand of customer i is a random variable;
- Stochastic times: the service time of customer I, and the travel time of edge (i, j) are random variables.

The SVRP refers to a family of problems that combine the characteristics of stochastic and integer programs, and are often regarded as computationally intractable (Gendreau *et al*., 1995). The random parameters may be the presence of customers, the nature of customer demand at a given location, the time such as service time, or travel time or windows time (Reimann, 2005). Because some of the data are randomised it is no longer possible to satisfy the constraints for all realisations of the random variables, and new feasibility and optimality concepts are required. With respect to their deterministic counterparts, SVRPs are considerably more difficult to solve and some of the properties that were valid in a deterministic context no longer hold in the stochastic case.

All of works mentioned above consider only CVRP and its extension in minimising cost, which is seen as the most important goal. However, solving CVRP in an emergency situation may need to consider a trade-off between the use of limited transportation resources and life-saving in the solution. Thus, a few CVRP studies in emergency circumstances such as natural and man-made disasters have been researched so far. In some situations, the highly unpredictable nature of emergencies leads to significant uncertainty, especially in demand. Vehicle routing in disaster relief should then consider the unique features of such an emergency. Therefore, studying the CVRP with random parameters is an essence in the real-world problems.

2.4.4 Solution methods for CVRP

Many different approaches have been developed to solve CVRP. In general, the approaches are divided into two classes: exact algorithms and heuristics algorithms (Chen *et al.*, 2006). Since the CVRP is considered as an NP-hard problem (Laporte, 1992; Liong *et al.*, 2008; Kanthavel and Prasad, 2011; Baldacci *et al.*, 2012), as Toth and Vigo (2014) report, no exact algorithm can effectively solve CVRP instances with more than 50 customers; thus, with larger instances, the CVRP may only be solved by heuristics algorithms. However, according to the VRP literature, not only heuristics are used to solve the CVRP, but also metaheuristics that generally produce better solutions, particularly in a more complex problem.

With regard to exact methods, these are used to obtain optimal solutions and guarantee their optimality. While heuristic methods generate high-quality solutions in a reasonable time for practical use, there is no guarantee of finding a global optimal solution.

In the class of exact methods, the most popular algorithms used for solving CVRP are the branch and X family, such as branch and bound, branch and cut, and branch and price. Exact approaches can be applied to small instances of complex problems (Talbi, 2009). Table 2-1 shows some popular NP-hard optimisation problems and the order of magnitude of the maximal size of instances where exact methods can solve the optimality. Some difficult problems can be solved by the exact algorithms on large networks of computers composed of more than 2,000 processors with more than 2 months of computing time (Mezmaz *et al*., 2007). This is consistent with Lin *et al.* (2009), where the computing time will dramatically rise when the problem size is large. Therefore, the computational time is a significant issue when using the exact methods for solving either very complex problems or large-instance problems, or both.

Optimization problem	**Quadratic assignment**	**Flow-shop scheduling**	**Graph coloring**	**Capacitated vehicle routing**
Size of instances	30 objects	100 jobs 20 machines	100 nodes	**60 clients**

Table 2-1: Order of magnitude of the maximal size of instances.

Source: Talbi, 2009

In the VRP literature, different variants of VRP were solved by using exact algorithms. Some noteworthy examples are branch and cut (e.g. Bard *et al*., 2002; Baldacci *et al*., 2008), branch and bound (e.g. Fischetti *et al*., 1994; Lau *et al*., 1997; Toth and Vigo, 2001), branch and cut and price (e.g. Fukasawa *et al.*, 2006). Unfortunately, exact algorithms for more complex VRP variants are not so well performing (Juan *et al.*, 2010), especially with large instances. Thus, heuristic methods are adopted in such an intricate problem or a problem with large instances in order to obtain better solution performance.

In the respect of heuristic methods, heuristics find good solutions to large-complex problem instances. Unlike the exact methods, heuristic approaches produce acceptable performance within a reasonable computing time, while they do not guarantee solution optimality (Talbi, 2009). In addition, most heuristic algorithms can be easily extended to account for the variety of real-life constraints (Laporte *et al.*, 2000).

Heuristic approaches can be categorised into classical heuristics and metaheuristics. The literature is also very rich on heuristic approaches for the CVRP, largely motivated by the limited results obtained by exact techniques in large realistic problems.

In classical heuristics, Clarke and Wright (1964) first proposed the use of savings algorithm for solving CVRP, and this heuristic method was later named as the Clarke and Wright Saving (CWS) algorithm. However, this algorithm was further modified by many researchers in order to obtain improved solutions (e.g. Holmes and Parker, 1976; Golden *et al.*, 1977; Paessens, 1988; Altinkemer and Gavish, 1991; Caccetta *et al.*, 2013). Most are aimed at reducing computation time and memory requirements, but these improvements are weakened due to the power of today computers. While some are intended to optimize the merger of routes through the use of a matching algorithm, although these modifications yield better solutions, this is at the expense of much higher computation time.

In recent years, metaheuristic approaches have been used to solve CVRP (Mester *et al*., 2007). Common metaheuristic approaches in CVRP include tabu search, simulated annealing, and genetic algorithm. For example, Ho and Gendreau (2006) applied the tabu search combined with path relinking to solve a large scale CVRP. Prins (2004) used genetic algorithm to solve CVRP. Wei *et al.* (2018) utilised simulated annealing algorithm with a mechanism of repeatedly cooling and rising the temperature for solving the CVRP with two-dimensional loading constraints. These state-of-the-art methods are increasingly used with combinations that could provide improved results. For instance, Lin *et al.* (2009) proposed an algorithm which takes the advantages of simulated annealing and tabu search combined with a local search for solving CVRP. Chen, *et al*. (2006) proposed a hybrid algorithm for CVRP. In the hybrid algorithm, discrete particle swarm optimisation combines global search and local search to search for the optimal results, and simulated annealing uses certain probability to avoid being trapped in a local optimum. These metaheuristic approaches can find near optimal solutions; however, they are rather complicated for implementation for CVRP.

According to the literature, the CWS constructive algorithm is probably the most cited heuristic to solve the CVRP (Laporte *et al.*, 2000; Juan *et al.*, 2010), probably due to its simplicity of implementation and efficient calculation speed. As CWS is a heuristic method, results obtained from the CWS algorithm are not guaranteed optimal or even near optimal (Rand, 2009). However, solution quality is not the most important aspect in the real-world VRP, but rather simplicity and flexibility of implementation (Juan *et al.*, 2010).

Furthermore, most of the routing optimisation in the VRP literature addresses only efficacy and efficiency objectives in the form of numerical results. Real-life VRPs encounter the spatial nature that is not considered by such problems. Thus, it would be worth including visualisation into VRP solutions in order to facilitate logistic operators to have better decision making.

2.5 Geographic Information Systems

Among the diverse applications integrated into the logistics sector through information technology, one that stands out most is the Geographic information systems (GIS), which are becoming powerful environments for decision making support in many fields of study. This section outlines the overall concept of GIS and its applications.

2.5.1 The fundamentals of GIS

The first GIS system was introduced in the 1960s. However, the large explosion in the use and development of GIS came in the mid 1990s, when the new generation of microcomputers and, at the same time an increasing amount of spatially identified socio-economic and environmental data, were made available (da Silva Júnior *et al.*, 2011). According to some definitions, a GIS is a powerful set of functionalities and tools to collect, store, retrieve, analyse, and display in the forms of geographically referenced and associated tabular attribute data (Gumusay and Sahin, 2009; Akay *et al.*, 2012; Malakahmad *et al.*, 2014; Krichen *et al.*, 2014; Leidig and Teeuw, 2015). This implies that a GIS user can expect support from the system to enter georeferenced data, to analyse it in various ways, and to produce presentations in the form of map visualisation from the data. Today, this generally involves the use of a software package (e.g. Quantum GIS, ArcGIS) for the creation and analysis of GIS data.

A GIS consists of three important components, which are hardware, software, and users (Delaney and Niel, 2007; Burrough *et al.*, 2015). While, Faiz and Krichen (2013) described the GIS components as more related to the aspect of how spatial data are developed via a process of data acquisition, processing, and results. In Faiz and Krichen's GIS component concept, a GIS not only deals with numerical data but frequently with geospatial data, which can be obtained from several mediums such as digitising, scanning, and remote sensing. Faiz and Krichen (2013) illustrated the main components of GIS as shown in Figure 2-2.

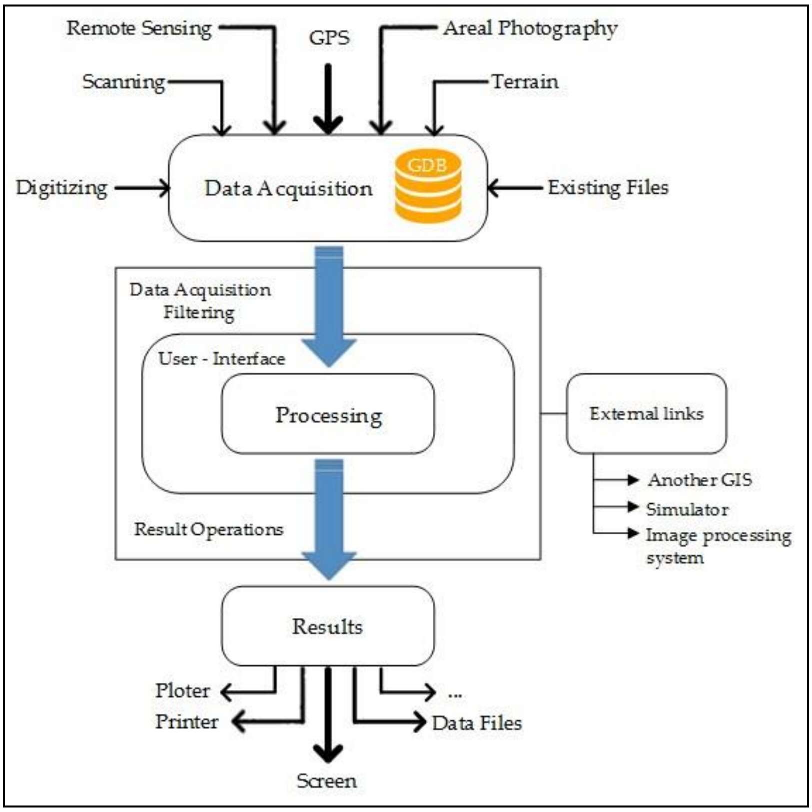


Figure 2-2: Main components of a GIS

Source: Faiz and Krichen, 2013

Spatial data in a GIS is created, analysed, and stored in many different formats. GIS data are usually stored in the form of two data structures which are raster and vector (Delaney and Niel, 2007). Vector data represent the world features using points, lines, and areas (polygons). Vector models are useful for storing data that has discrete boundaries, such as country boundaries, roads, and land parcels. Each feature (point, line, or polygon) can have values to describe the feature characteristics (e.g. name, area, etc.). This description of the feature is called attribute data, which is usually presented in tubular format.

Raster data, in contrast, are made up of a matrix of cells organised into rows and columns in which each cell contains a value representing information such as elevation. Raster data are cell-based and this data also includes aerial and satellite imagery. There are two types of raster data: continuous and discrete. An example of discrete raster is population density, while continuous data examples are temperature and elevation measurements.

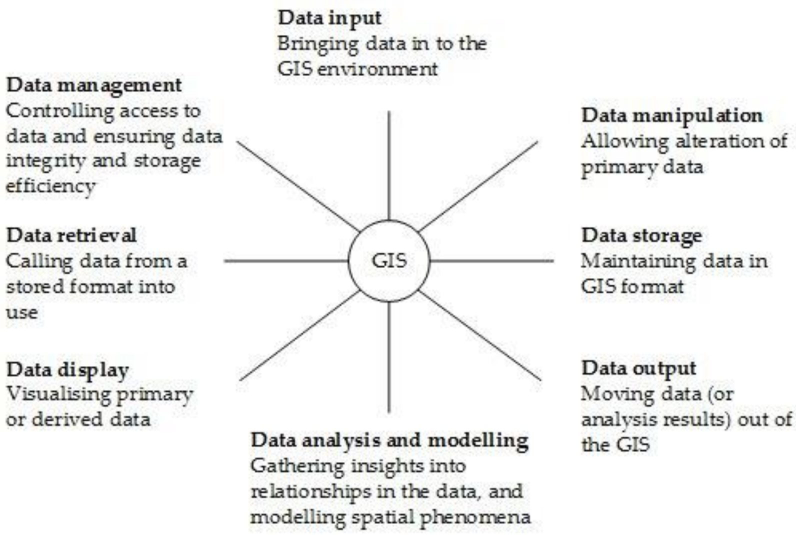


Figure 2-3: GIS functional elements.

Source: Delaney and Niel, 2007

A GIS combines computer-mapping functionality that controls and displays spatial data, with database-management functionality to manipulate and distribute data. The basic GIS functionality includes data input, data storage, data management, data retrieval, data manipulation, data analysis and modelling, data output and display (Delaney and Niel, 2007). Figure 2-3 shows the brief duty of each functional element of a GIS.

The wide range of functions available within GIS provides useful tools that can be used in many disciplines, among those tools, free GIS software packages exist, and are growing in number. According to Leidig and Teeuw (2015), some GIS free and open source software (FOSS) have an advantage over the leading commercial GIS such as ArcGIS. However, they have their own advantages and disadvantages as compared in Figure 2-4. For example, commercial GIS software is most suitable for organization level use, and it is advantageous in terms of analytic capabilities and technical support, whereas it is much easier to customise, scale and adapt to existing open software systems.

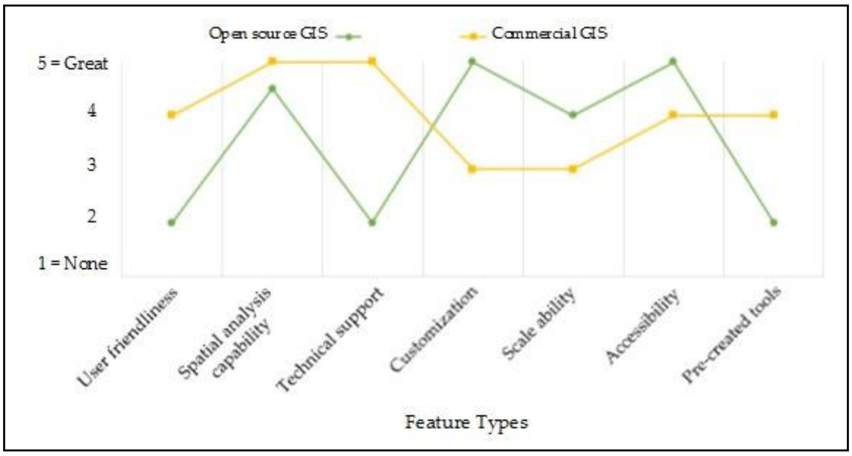


Figure 2-4: Features comparison between freeware open source and commercial GIS software.

Source: Intetics, 2016

The choice of FOSS or commercial GIS mapping software depends on a project. Both FOSS and commercial GIS software can be viewed as spatially referenced databases with the facility of displaying information as maps and performing analysis such as extraction, intersection, overlaying, and appending. Commercial GIS software provides network-based spatial analysis and application of the ArcGIS Network Analyst (Akay *et al.*, 2012), which provides the capabilities for solving route, service area, closest facility, location-allocation, origin-destination cost matrix, and vehicle routing problem. This allows users able to build a model of a network dataset and perform analyses on the model. However, ArcGIS can be a budget barrier for low or middle income countries because this proprietary software can cost between US$1,000 - US$10,000 per year (Leidig and Teeuw, 2015).

2.5.2 The applications of GIS

GIS technologies have been widely applied in all scientific fields and practical activities. GIS is used by businesses to provide solutions for customer and market analysis, environmental assessment, risk analysis, territory and asset management, and logistics. However, this section does not provide every aspect of GIS applications, although some examples are given as follows.

GIS is being recognised as an important tool for natural resource management. The use of GIS in the natural environment includes a broad spectrum including visualisation of natural resources, visualisation of pollutant concentrations in the environment and their spatial distribution (Fisher *et al*., 2006). Moreover, GIS is commonly used for planning and implementing environmental management processes, e.g. water divide areas (Rybaczuk, 2001), hazard monitoring, area usage modelling (Zeilhofer *et al.*, 2011), or forest protection against hazards (Teich and Bebi, 2009).

Many researchers have integrated indigenous knowledge (IK) into GIS for the purpose of environmental management. For example, Gonzalez (1995) applied integrated IK and GIS for natural resource management by using aerial photographs and satellite images for mapping community situations and aspirations in the Philippines. Furthermore, Puginier (2001) used local knowledge in GIS as a communication tool for community level land use planning in northern Thailand.

A GIS can also play a vital role in disaster management. The risk analysis of natural disasters is unimaginable without the support of GIS (Gigović *et al.*, 2017). Natural disasters are multidimensional phenomena with a spatial dimension, which makes GIS very applicative for such analysis (Zerger, 2002; Bathrellos *et al.*, 2017), thus developing GIS-based approaches for disaster management has been receiving a greater level of attention among researchers.

For example, in hydrological modelling, GIS can be used to construct flooding projection models in catchments, and to prepare and analyse multi-scale and multi-source spatial data (Merwade *et al*., 2008; Gallegos *et al*., 2009). In the literature, there have been many studies showing the successful use of GIS-based hydrological models for flood prediction in urban areas (Samarasinghe *et al.*, 2010; Uddin *et al.*, 2013). For example, Gigović *et al.* (2017) propose a GIS multi-criteria methodology for hazard zone mapping of flood prone areas in urban locations. Moreover, Dang and Kumar (2017) utilised remote sensing techniques coupled with GIS-based hydrological modelling to identify flood risk in the urban areas of Ho Chi Minh City.

Regarding tsunami hazard assessment, GIS has been widely used to create accurate data for tsunami inundation modelling and for visualizing and mapping the extent of inundation (e.g. McAdoo *et al*., 2007; Schlurmann *et al.*, 2011; Suppasri *et al*., 2011). Additionally, Omira *et al.* (2010) and Murthy *et al.* (2011) studied possible risks of an earthquake and subsequent tsunami flooding on coastal areas by applying numerical models and GIS. Furthermore, Sirikulchayanon *et al*. (2008) proposed a GIS-based approach to examine the impact of the 2004 tsunami on mangrove vegetation. The approach integrates GIS proximity analyses with change detection methods in remote sensing for explaining multiple buffer distances from the shoreline to homogeneous subareas.

Recent trends towards the development of GIS have prompted researchers in the OR field. It has proven its efficiency in various areas of study by solving different kinds of problems in several application domain, which has made it so popular and widespread. However, GIS encounter some challenges in OR studies. For example, GIS produces a map but cannot evoke the optimisation aspect of the distribution problems, and vice versa; the optimisation is unable to result in a map (Tlili *et al*., 2013). To avoid such situations, the use of GIS must be consolidated. Optimisation offers various tools that can widely contribute to improving the GIS performance while tackling and solving more complicated problems (Li *et al.*, 2011), as well as in multi-criteria decision making (Malczewski, 2006).

Previous research has explored the coupling of decision-making systems with spatial databases for solving vehicle routing problems (Tarantilis and Kiranoudis, 2002; Keenan, 2008). In some cases, research has explored vehicle routing in real time solutions that allow for routes to be updated dynamically as a vehicle travels across a network (Ichoua *et al*., 2000; Gendreau *et al*., 2001). Real-time solutions allow for vehicle movement within a network, changing network pathways or changing conditions along the pathways, and for potential alterations in a destination to be accounted for in the evaluation and selection of a new route.

2.6 Chapter Summary

In this chapter, disasters are firstly reviewed in order to categorise them into groups based on their speed and cause. Logistics effort is also combined in each disaster category to obtain more understanding of the relationship between a disaster type and its need for relief logistics. In addition, the appraisal of the disaster management cycle provides the knowledge of what mechanisms are needed in each disaster phase. As a result of disaster review, an occurrence of a tsunami is a natural-sudden-onset disaster that needs a high level of logistics effort, particularly in the preparation and response phases.

The next subject to review is therefore tsunami characteristics and hazard assessment. With this review, it gives essential information regarding tsunami, in relation to not only its characteristics, such as tsunami wave inundation, but also the past consequences in Thailand such as tsunami direction and run-up elevation. Furthermore, the current developments for tsunami prevention and mitigation in Thailand are disclosed as a result of the review. The studies of tsunami hazard assessment in the past have revealed many aspects such as methodologies, data, and techniques. As a result, the most efficient technology for assessing tsunami hazard is to use GIS and remote sensing data that can provide effective outputs in the form of thematic map with perhaps useful information of population distribution in the hazard areas. The information of hazard regions and vulnerable people exposed to tsunami then can facilitate planning and managing relief operations in the tsunami response phase.

Of importance in the tsunami response, is the logistics aspect. The review of humanitarian logistics, therefore, is inevitable. This part begins with the clear term of humanitarian logistics followed by a question of why this logistics in the disaster context has to be improved. According to the literature, this question has arisen due to the increasing number of natural disasters across the globe and subsequent poor relief mechanisms for people in need. Furthermore, compared to commercial logistics, humanitarian logistics faces more complexities in a disaster situation, especially in relation to unpredictable demand, which critically depends on the affected population.

Therefore, the next subject for review is estimates of population affected by disasters. Techniques for estimating population are discussed particularly in a small area where census data is perhaps not capable of providing an accurate and timely snapshot. In addition, the use of population estimation is reviewed in several disciplines particularly in emergencies where humanitarian response requires most quick and accurate estimates of the population affected. As a result, the challenges of estimating populations in the disaster context are discussed, and one of the best solutions found in the literature is to estimate the size of vulnerable people in the hazard assessment process. In addition, the supporting data, such as population-relevant variables and GIS and remote sensing data are very useful for estimating population in a disaster region. As the affected numbers can be interpreted to demands in the disaster relief context thus, obtaining accurate affected estimation would contribute to better decisions to be made for routing optimisation in the last-mile distribution.

The last two parts of this chapter also reviewed the CVRP and the GIS, which are the core components of this research. The CVRP is introduced to understand its concept and also to discuss its extensions that are used in the real-life distribution. Furthermore, a number of solution approaches are explored through the literature in order to find the most suitable optimisation method for the CVRP.

With regard to GIS, there are several academic papers using GIS technologies especially in the GIS and remote sensing literature. However, the fundamentals of GIS is firstly reviewed and followed by its applications, which are studied in many scientific and practical activities. Of importance in using GIS and remote sensing in such activities is the need to produce maps of visualisation for efficient analyses and better decision making, especially in the OR domain.

Applying both CVRP and GIS has increasingly received interest in recent researches. Nevertheless, there is little attention among researchers in combining GIS and CVRP optimisation in the disaster context. As a result, this research aims to develop a mechanism by integrating both principal subjects for facilitating humanitarian logistics in a case of tsunami inundation.

Chapter 3: Research Methodology

3.1 Introduction

This research studies the combination of Geographic Information Systems (GIS) and the Capacitated Vehicle Routing Problem (CVRP) optimisation to develop a decision support system (DSS) for humanitarian logistics in case of a tsunami inundation. This research is conducted because that there is no existing GIS-CVRP integrated structure for disaster management that can guide relief logistics in Thailand, particularly in a tsunami event. Therefore, this research proposes a GIS-based DSS by coupling the CVRP algorithm to enhance logistics mechanisms in the aftermath of a tsunami.

This chapter starts by describing the research framework in section 3.2, followed by the material sources in section 3.3. The means that contributed to the development of the DSS are explained in section 3.4. Finally, section 3.5 summarises this chapter.

3.2 Research Framework

After the Indian Ocean tsunami in 2004, Thailand established an infrastructure to prevent and mitigate future tsunami strikes. In particular, it has put into place a real-time tsunami warning system along the coastal areas vulnerable to tsunami. If a tsunami occurs, the warning centre can provide tsunami information to its notice stations such as the possible height of the tsunami surge and its estimated landfall time. An evacuation plan also has been implemented, including signs showing a route to an evacuation site.

This research studies a further step in the aftermath of a tsunami, which is how to serve people gathering at the evacuation sites to which the supply centre would dispatch first relief efforts in a timely manner. If a tsunami occurs and destroys facilities, people in the affected area would have to stay in the evacuation shelters perhaps for a very long time. This is due to the nature of earthquakes and subsequent tsunamis as an unknown number of aftershocks are likely to happen. Also, survival resources may be limited for evacuees as a tsunami could destroy everything in its path.

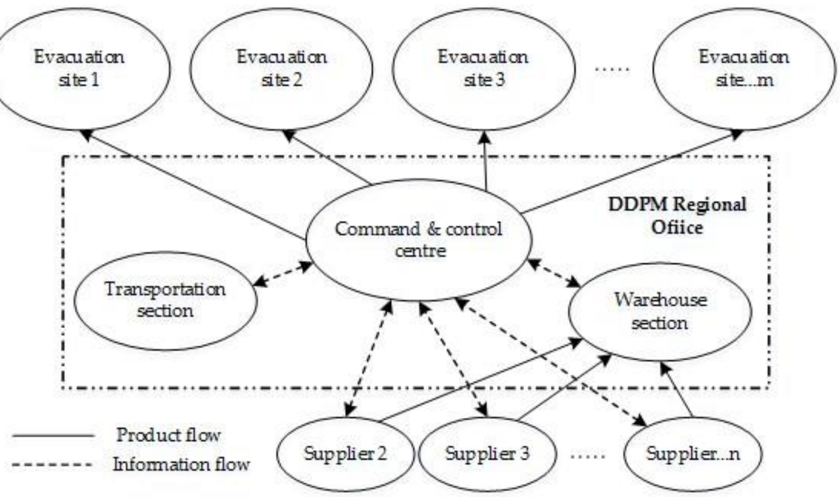


Figure 3-1: Logistics flow after a tsunami occurrence.

After an assessment by the Department of Disaster Prevention and Mitigation (DDPM) that relief logistics are required, disaster relief stakeholders, mainly the DDPM Regional Office, would be charged with alleviating suffering. The framework of the DDPM Regional Office's logistics flow is illustrated in Figure 3-1. This study focuses on relief distribution using the transportation resources available at the DDPM Regional Office.

To improve the logistics mechanism, this research proposes an integration of GIS and CVRP optimisation to form a GIS-based DSS, and uses Phuket, Thailand as a case study. Integrating GIS and CVRP optimisation would create a spatial DSS, an efficient tool to facilitate decision-making in terms of distribution management to alleviate the people's suffering. Figure 3-2 shows the overall structure of integrating GIS and CVRP optimisation in this study.

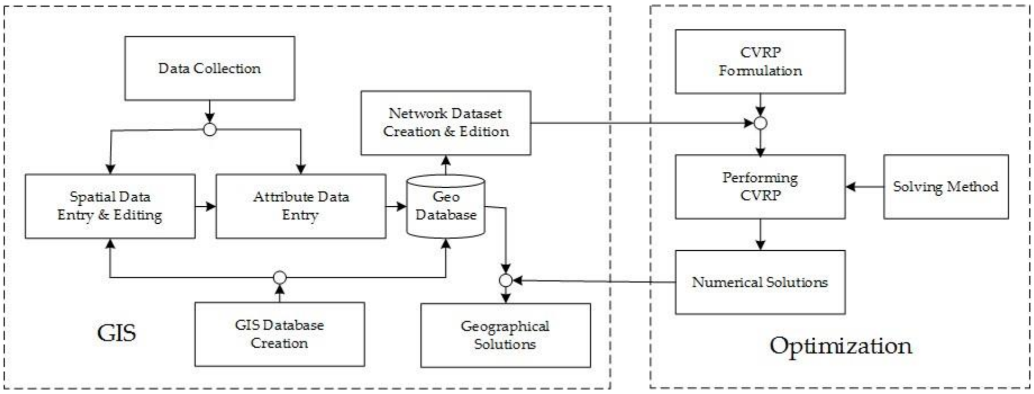


Figure 3-2: Integration structure.

Figure 3-2 illustrates the integration of the two systems. Firstly, in the GIS environment, GIS data are acquired from different sources and categorised into spatial and attribute data. The GIS data are imported into the ArcGIS platform and edited using ArcMap functionalities. Then geographic data are stored in the geodatabase for further editing and data management, whereby a network dataset is created and used for the optimisation section.

In the optimisation section, the system uses the GIS dataset including street-network and evacuation-site data. The cost matrix and position of evacuation locations, which are based on such data, respectively, are important ingredients for performing the CVRP optimisation. Using a heuristic approach, the CVRP then is solved, resulting in numerical solutions which are automatically transferred to the ArcGIS platform as visualization maps.

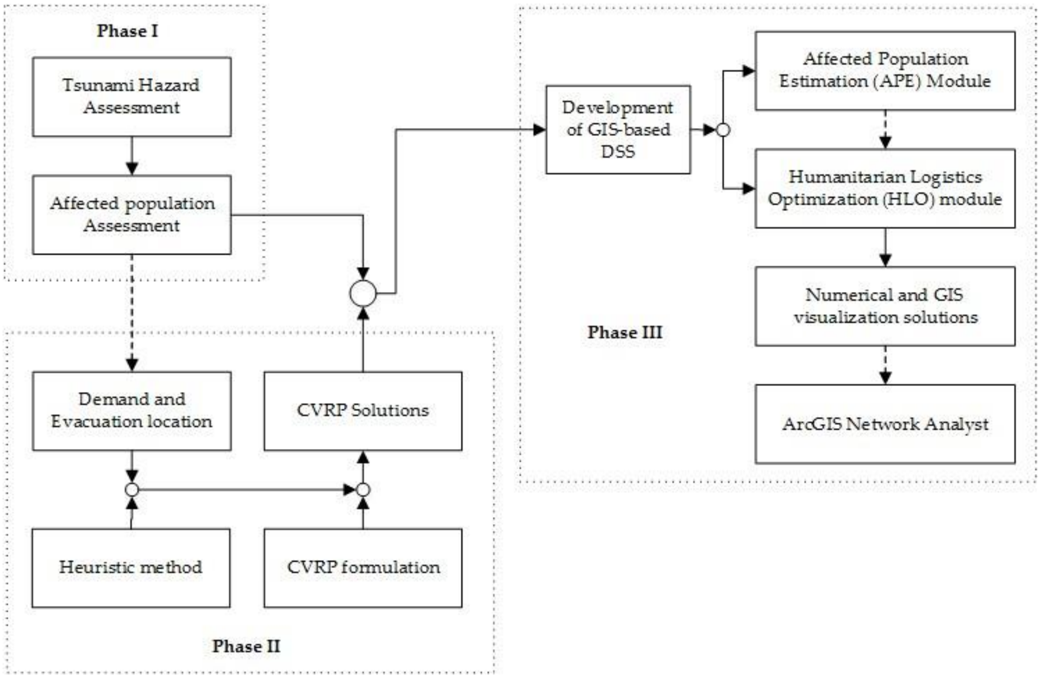


Figure 3-3: Research framework.

The research framework consists of three main phases (see Figure 3-3): GIS-based population assessment, CVRP with simulated demand and development of a DSS by combining GIS and CVRP optimisation. Firstly, the work is related to presenting the approach for estimating the population affected by a tsunami inundation. In this stage, a combination of spatial interpolation techniques is operated based on the ArcMap functionality. In the second phase, the CVRP is modelled and solved heuristically to obtain solutions to be used as a distribution plan of relief logistics. Lastly, the GIS-based DSS is developed based on the algorithms proposed in the first two phases. Both numerical and geographical results are generated in this phase to support making decisions in the form of instant results and later in the form of GIS materials for further analysis in the ArcGIS environment.

The framework will be simply understood and reflects the activities to be carried out in this research. Visualization maps generated using GIS will help a logistics operator or decision-maker plan relief distribution efficiently and effectively. The criteria are especially important to ensure that the proposed system is easily and accurately implemented by the local relief distribution centre.

3.3 Material Sources

The main purpose of this section is to explain the use of the materials essential in this research. The resources consist of three main measures. Firstly, the ArcGIS 10.3 application is needed to edit data, perform spatial analysis and produce visualization maps. Secondly, this study requires GIS and document data collected from different sources. Lastly, IntelliJ IDEA software is needed to implement computer programming languages to develop the proposed DSS. An explanation of each component follows.

3.3.1 Esri ArcGIS 10.3 software

Recently, several organizations used GIS to obtain cartographic information to make better decisions. GIS represents real-world objects on maps so they can be analysed using spatial tools for performing desired tasks. ArcGIS is a proprietary GIS software which belongs to the Environmental Systems Research Institute (Esri) software company. It provides a scalable framework for creating, managing, storing, analysing and visualising geographic data with maps. ArcGIS is most suitable for organization level use, and it is advantageous in terms of analytic capabilities and technical support. For example, ArcGIS has a Network Analyst extension that provides network-based spatial analysis tools for solving complex routing problems, enabling organizations to accurately represent their unique network requirements.

ArcGIS software includes a suite of integrated applications such as ArcMap, ArcCatalog and ArcToolbox. This research, however, uses only ArcMap and its Network Analyst extension for implementing the proposed DSS.

3.3.1.1 ArcMap

ArcMap is the main component of the ArcGIS suite of geoprocessing programs. It is used to view, edit, create and analyse spatial data. The ArcMap working model consists of a map display area, table of contents, toolbars and menus for working with the GIS feature class and its attribute data. ArcGIS extensions enable users to expand the functional capabilities with the GIS toolbox for geoprocessing, three-dimensional visualization, geostatistical analysis, etc.

3.3.1.2 Network Analyst

ArcGIS Network Analyst is a powerful extension for managing routing problems. It is used for network-based spatial analysis, using features such as route, closest facility, service area, origin-destination cost matrix and location-allocation. Network Analyst can benefit organizations in many aspects including transport, public safety, health care and disaster management.

With respect to disaster management, this study employs ArcGIS Network Analyst to visualise the set of relief routes obtained from the CVRP optimisation solver. The delivery routes can be displayed in sequence starting from the relief distributor to a set of demand nodes based on the real-world street network in the study area. In addition, Network Analyst enables the decision maker to use the new route feature to do a re-routing to avoid a road which is flooded and cannot be used for deliveries. As a result, it can efficiently facilitate decision making before and during the disaster response phase.

3.3.2 Dataset and data collection

The datasets used in this case study include digital elevation and administrative boundaries data, street footprints data, geographic and demographic data and evacuation location data. The first three datasets are in the GIS file formats. The digital elevation data in this case study can be downloaded at no cost from the USGS Earth Explorer portal in the form of a digital elevation model (DEM), which represents the continuous elevation values over a terrain's surface. For this case study, the DEM, with a resolution of 30 metres, is the product of the Shuttle Radar Topography Mission (SRTM), which is a National Aeronautics and Space Administration (NASA) mission aiming to obtain earth surface data by remote sensing technology. The availability of SRTM gives users good quality DEMs for performing various types of topographic and elevation analysis.

The administrative boundaries and street footprints are in the format of a vector polygon and a vector line, respectively. These GIS shapefiles can be directly downloaded for free from the MapCruzin website, which provides the detailed country-level shapefiles for GIS. The quality and accuracy of the data and sources stocking this portal are recognised as reasonable for educational research. However, in this chapter, these data are revaluated by superimposing them with areal photographs of the study area. The result has acceptable accuracy as shown in Figure 3-4.

Demographic data coupled with a digital map for small-area analysis such as a census block have not been developed in Thailand. Thus, the most detailed population data available for digital maps are limited to the administrative boundaries of sub-districts. The population data for 2016 are taken from the DOPA, Ministry of Interior, Thailand.

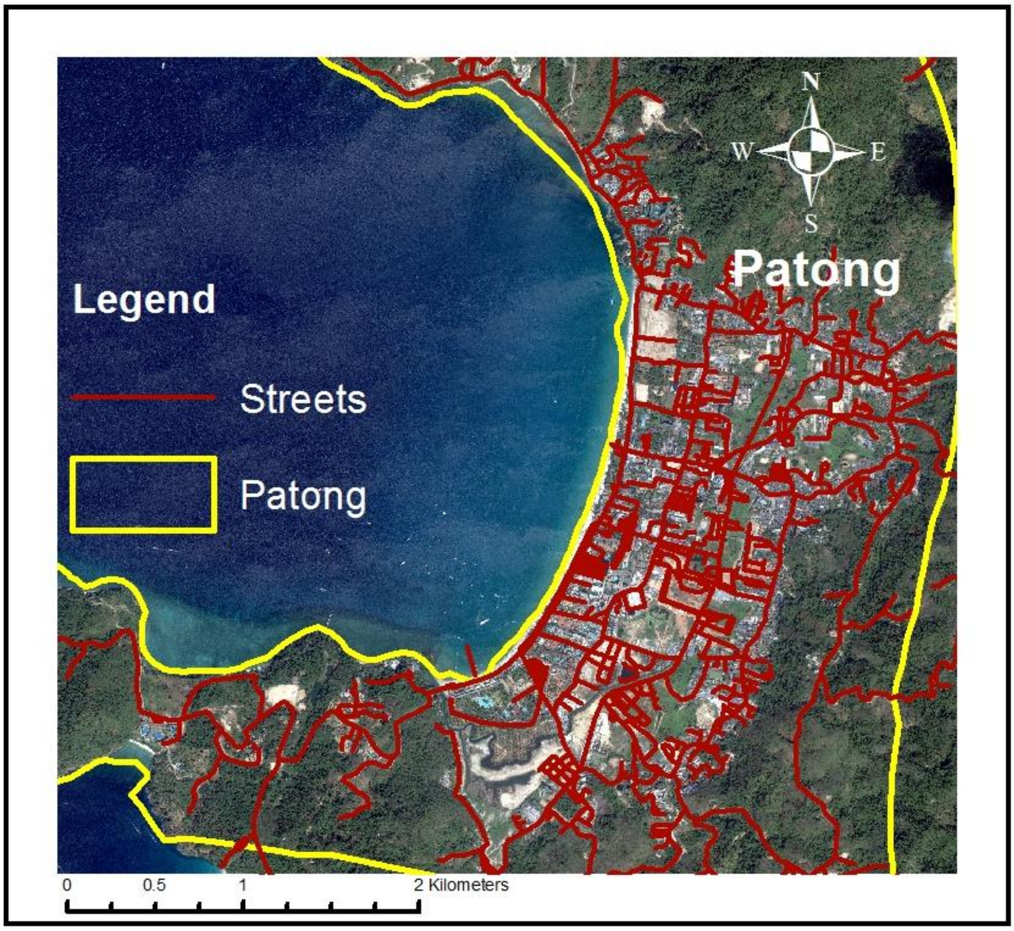


Figure 3-4: The evaluation of street footprints.

The data for the evacuation locations are obtained from the Department of Disaster Prevention and Mitigation (DDPM), Ministry of Interior, Thailand. As a result of the Asian tsunami in 2004, Thai authorities have developed tsunami warning systems as well as evacuation plans including evacuation routes and safe places for evacuees. The evacuation locations are prearranged, utilising local government buildings/areas such as schools, temples and mosques, and other public spaces which are expected to be safe from tsunami flood inundation. However, in order to use the data in a spatial analysis, the coordinates of the evacuation sites have to be converted to the format of the vector point in the GIS environment.

GIS Data	Data format	Source	Portal	Method
Phuket Digital Elevation Model (DEM)	30-meter Resolution Raster	USGS Earth Explore	www.earthexplorer.usgs.gov	Download
Patong satellite images	1-meter Resolution Raster	GISTDA	www.gistda.or.th	Official request
Phuket administrative boundary	Vector	DIVA-GIS	www.diva-gis.com	Download
Street network	Vector	Map Cruzin	www.mapcruzin.com	Download

Table 3-1: GIS data sources.

All the data used in this research were collected from public sources at no cost. Most GIS data were downloaded from web portals, as summarised in Table 3-1, while other essential data were provided by Thai government organizations, as shown in Table 3-2. Some data providers required official authorisation; such data were requested on behalf of the Royal Thai Air Force.

Document Data	Data format	Source	Portal	Method
Phuket population	Tabular	Department of Provincial Administration	www.dopa.go.th	Download
Phuket tourist	Tabular	Department of Tourism	www.tourism.go.th	Download
Phuket evacuation location	Tabular	Department of Disaster Prevention and Mitigation	The master plan for tsunami	Official request
Phuket tsunami risk level	Tabular	Department of Disaster Prevention and Mitigation	The master plan for tsunami	Official request
Relief supply facility, Phuket office	Descriptive	Department of Disaster Prevention and Mitigation	-	Interview

Table 3-2: Document data sources.

All the data collected contributed to achieving the research goals. The purpose of the data is explained as follows.

1) GIS data

➢ Digital Elevation Model (DEM) of Phuket

DEM data are digital data in a raster format that has information about coordinate positions (x, y) and elevation values (z) in each pixel. In this study, the DEM data were used to describe the topographic conditions in the study area.

The DEM data were derived from the USGS Earth Explorer web portal. DEM represents the continuous elevation values over a terrain's surface. The data acquired for this study has a resolution of 30 metres and is the product of the Shuttle Radar Topography Mission (SRTM), which is a National Aeronautics and Space Administration (NASA) mission aimed at obtaining earth surface data using remote sensing technology. The availability of SRTM gives users good quality DEMs for performing various types of topographic and elevation analysis.

The DEM data were used to classify inundation zones in the hazard assessment (see Figure 3-5). To calculate inundation areas, this classified data must be converted to the form of vector data, which is later used for spatial interpolation in the population estimation stage.

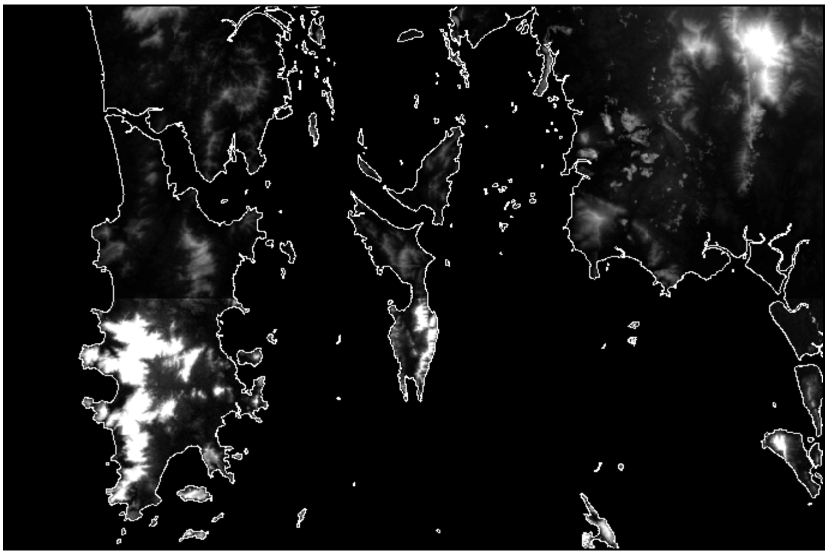


Figure 3-5: DEM data of the study area.

- Patong satellite images

To observe the 2004 tsunami's impact on Phuket, satellite images were provided by the Geo-Informatics and Space Technology Development Agency (GISTDA), Thailand. Because the data are restricted as part of a proprietary product, only a part of the study area (Patong sub-district) was supported so that the impact of Patong before and after the tsunami event in 2004 could be witnessed in this study.

- Administrative boundaries of Phuket

Phuket is divided into three districts, which are further subdivided into 17 sub-districts. Their boundaries in the format of GIS data were derived from DIVA-GIS, a free computer program for mapping and geographic data analysis. The data are in the form of polygon vector data, which can be used to represent Phuket and its subdivisions. The boundaries of the study area are necessary because this GIS feature class has geometry and attribute data which describe that geometry such as area name, address, position and population as shown in Figure 3-6. Thus, the attribute data of the geometry can be used to perform spatial queries and analyses. Therefore, having boundary data was an important element for querying and calculating attribute data for population estimation.

Table

Phuket boundary

OBJECTID *	Shape *	NAME_1	NAME_2	NAME_3	ENGTYPE_3	SubDist_Pop	Shape_Length	Shape_Area	Area_Sqm
1	Polygon	Phuket	Kathu	Kamala	Sub district	6898	21766.897424	18839767.727964	18.839768
2	Polygon	Phuket	Kathu	Kathu	Sub district	28241	26735.237953	40271837.024729	40.271837
3	Polygon	Phuket	Kathu	Pa Tong	Sub district	20628	26984.862295	19185093.680673	19.185094
4	Polygon	Phuket	Muang Phuket	Chalong	Sub district	24733	24464.059775	26020161.166525	26.020161
5	Polygon	Phuket	Muang Phuket	Ka Ron	Sub district	8147	33857.967202	22408761.310216	22.408761
6	Polygon	Phuket	Muang Phuket	Ko Kaeo	Sub district	13984	36034.367202	24870180.380393	24.87018
7	Polygon	Phuket	Muang Phuket	Ratsada	Sub district	46865	46780.027712	33226547.661979	33.226548
8	Polygon	Phuket	Muang Phuket	Rawai	Sub district	17586	94418.258675	40747262.772626	40.747263
9	Polygon	Phuket	Muang Phuket	Talat Nuea	Sub district	22314	9116.050821	3232877.746254	3.232878
10	Polygon	Phuket	Muang Phuket	Talat Yai	Sub district	56609	11752.227838	5229520.521004	5.229521
11	Polygon	Phuket	Muang Phuket	Wichit	Sub district	48628	54226.545368	37712178.799439	37.712179
12	Polygon	Phuket	Thalang	Choeng Tale	Sub district	18275	33957.680222	29773562.143488	29.773562
13	Polygon	Phuket	Thalang	Mai Khao	Sub district	13005	39950.385432	49165419.224004	49.165419
14	Polygon	Phuket	Thalang	Pa Khlok	Sub district	15960	70728.171927	68613472.352411	68.613472
15	Polygon	Phuket	Thalang	Sakhu	Sub district	6345	22535.923678	22919789.242541	22.919789
16	Polygon	Phuket	Thalang	Si Sunthon	Sub district	23611	35564.876946	44672590.444137	44.67259
17	Polygon	Phuket	Thalang	Thep Krasatti	Sub district	22340	39990.414507	67521207.917574	67.521208

0 (0 out of 17 Selected)

Phuket boundary

Figure 3-6: Data of study area boundary.

- Phuket street network

The street data of Phuket, which is the polyline feature of the GIS vector data, were used to represent the real-world network streets of the study area in the GIS environment. Figure 3-7 shows the shapefile of road networks derived from MapCruzin, which is an online GIS service. The street volume and an area boundary of the study area were used as input data in the street-weighted interpolation technique to estimate the population. Moreover, the route solutions that were solved must be displayed based on the road network to enable the decision maker to visually manage the routing maps in the ArcGIS platform.

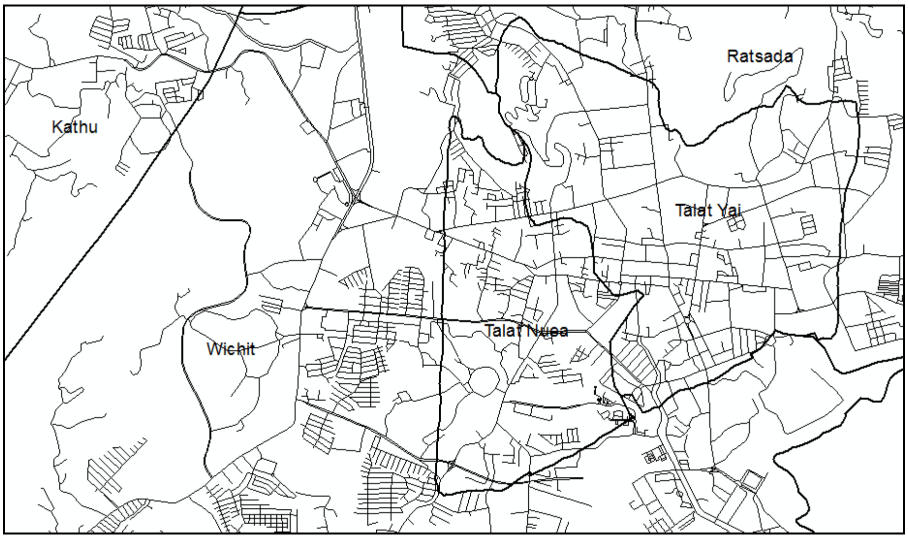


Figure 3-7: Data of street network in the study area.

2) Document data

- Phuket population and tourist data

Phuket province is the country's largest island with a population of 394,169, according to the 2016 administrative record provided by the Department of Provincial Administration (DOPA), Ministry of Interior, Thailand. As this is one of the hazard areas, the people in Phuket are vulnerable to tsunamis. Hence, the population data obtained in this research was essential for estimating the number of people who would be affected by a tsunami inundation, depending on the tsunami severity.

In addition to the local population, tourist figures are considered in estimating the population affected by a tsunami. In a world tourist spot like Phuket, a dynamic population with tourists would have a major impact on a snapshot of the estimated population. However, determining an exact number of tourists visiting Phuket at a particular time is almost impossible. Thus, this study estimated the number of tourists using historical data from 2009 to 2016, supported by data from the Department of Tourism (DOT), Ministry of Tourism and Sports, Thailand. These data were further statistically analysed and added to the local population to estimate the total population affected by a tsunami inundation.

- Evacuation and tsunami risk data

After the tsunami event in 2004, the Thai government realised that tsunamis have the potential to cause widespread destruction and affect a large number of people. Hence, the DDPM established a master plan for dealing with this type of disaster.

To create the plan, the areas affected by the 2004 tsunami were summarised in terms of the impact the tsunami caused. For example, the DDPM documented impact data and tsunami characteristics such as casualty numbers and tsunami surge height. Based on historical data, the DDPM identified tsunami hazard zones, each of which has hazard markers with information including the depth of the tsunami wave. This information enabled the DDPM to create an evacuation infrastructure including tsunami warning towers, tsunami evacuation signs and safe places for evacuees.

To achieve the aim of this study, the DDPM's tsunami information was officially requested for use as essential data, including tsunami risk level and potential depth of tsunami wave at each hazard point. These data are important to model tsunami hazard areas in the GIS environment. With respect to the developed infrastructure, the geographic coordinates of the evacuation locations are used as demand nodes, which are significant for both population estimation and CVRP optimisation.

- Relief supply facility (DDPM Regional Office no. 18, Phuket)

In addition to the tsunami risk data, the characteristics of the DDPM relief supply centre in Phuket, namely DDPM Regional Office No. 18, were needed for this study. These data were derived through an interview with the director of the regional office (see the interview questions in the Appendix D). As a result, the details of the relief facilities were obtained, including its geographic location, vehicle capacity, current supply methods and, most importantly, decision-making technology requirements, which became the aim of this research.

3.3.3 IntelliJ IDEA Community Edition

IntelliJ IDEA software is a special programming environment, a premier integrated development environment (IDE) for Java and other programming languages such as Python. The application is loaded with a set of features and functionalities that are great for software development. Moreover, it is designed to improve productivity by delivering the most intuitive code assistance for all frameworks. This software therefore is suitable for developing computer applications.

IntelliJ IDEA Community Edition is the open source version of IntelliJ IDEA. It can be downloaded for free and is open for contributions by community members. The application is built on top of the IntelliJ platform, which is fully open source.

This research used IntelliJ IDEA Community Edition to develop the GIS-based DSS, which is split into two subsystems: Affected Population Estimation (APE) and Humanitarian Logistics Optimization (HLO). Python programming language was coded in the APE environment because it is accepted as the scripting language of choice for geoprocessing in the GIS environment. Java programming language was implemented in the HLO for coding the proposed heuristic algorithm.

3.4 Methods

To operate the humanitarian logistics with efficiency and effectiveness, a spatial DSS was proposed in this research. Sub-districts were used as the basis for database development and management. The data preparation method and the DSS development are explained in the following sections.

3.4.1 Data preparation

Prior to developing the GIS-based DSS, both the GIS data and document data were prepared using different methods. By having data ready for the study experiments, the GIS data and related document data were prepared in the ArcGIS platform, while other data were operated in a separate environment.

3.4.1.1 Vector map preparation

In this study, most of the digital data such as administrative boundaries and the street network had to be in a vector shapefile format. These data were derived in the form of the whole country and then clipped using ArcMap functions into the boundary of the study area as shown in Figure 3-8.

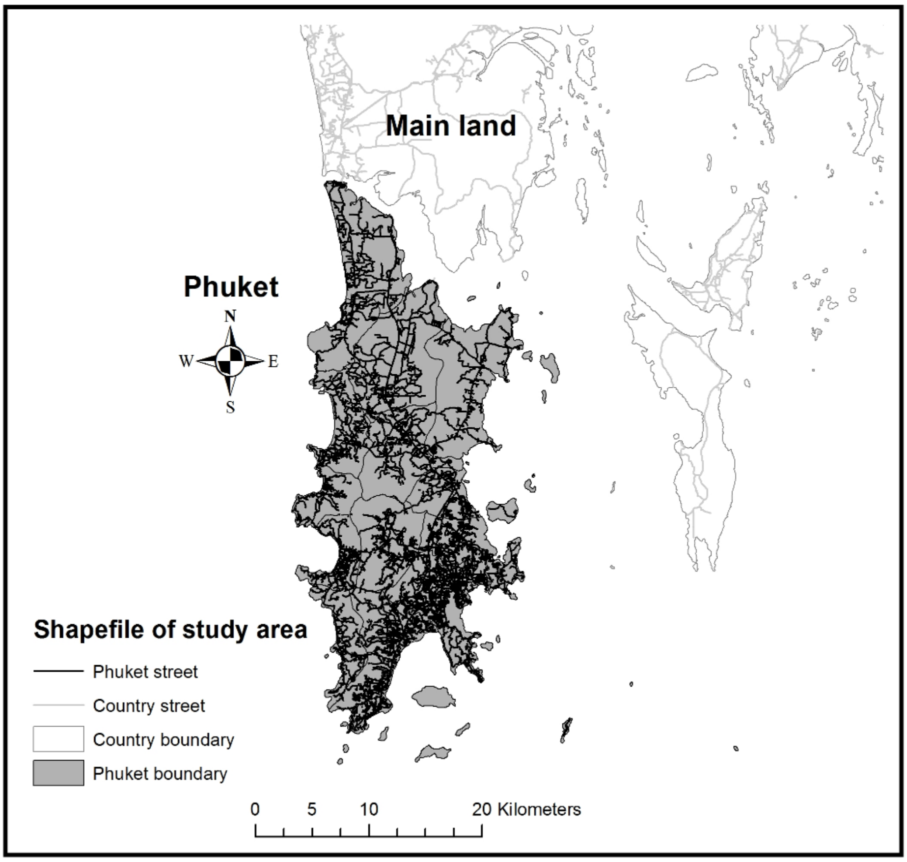


Figure 3-8: Vector map preparation.

3.4.1.2 DEM preparation

The DEM was clipped to the study area using the vector shapefile created earlier. In this stage, raster processing in ArcMap was used in a clip operation between the DEM layer, which is a raster format, and the boundary layer, which is a vector format. As a result, the DEM of the study area, as shown in Figure 3-9, was arranged for further analysis.

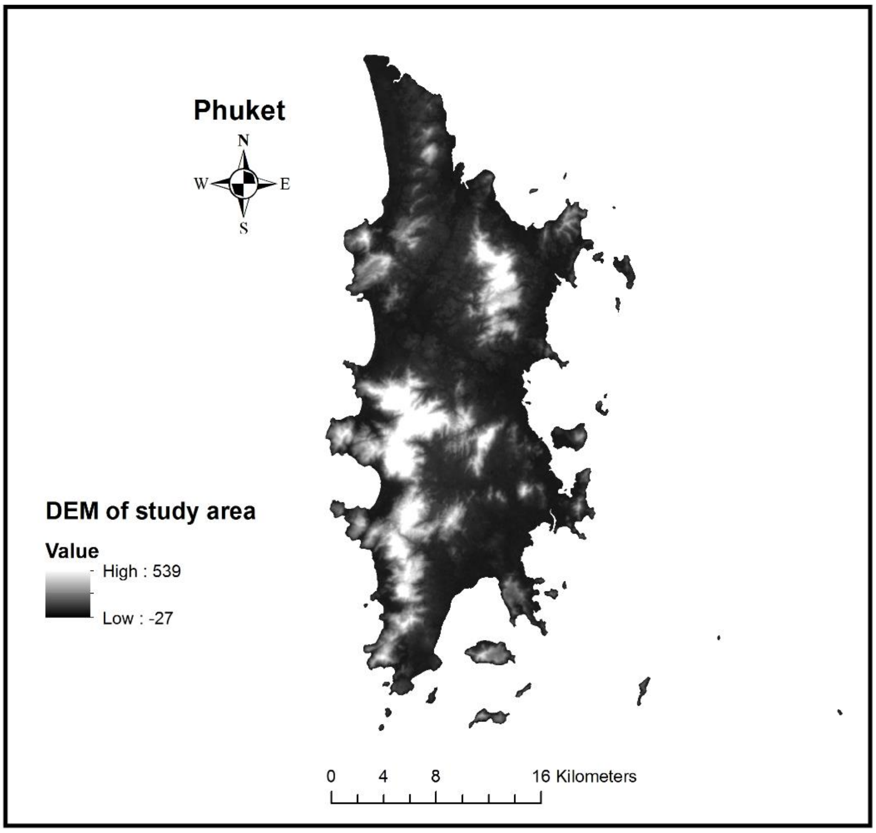
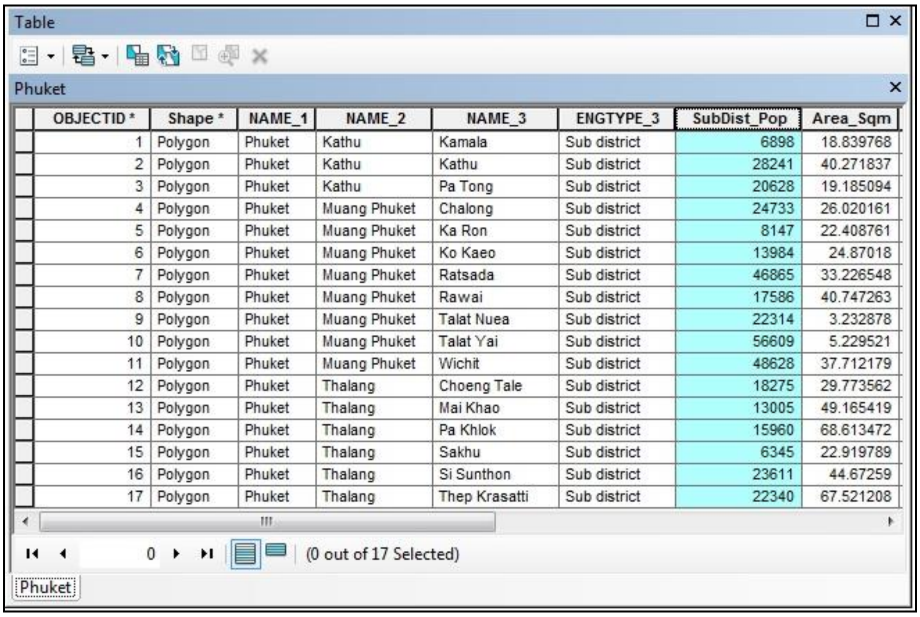


Figure 3-9: DEM preparation.

3.4.1.3 Attribute database preparation

In this stage, population data derived from the DOT was updated in the attribute table of the Phuket boundary shapefile. This process must be operated in the ArcMap environment. In the attribute table, population and town area fields were created, followed by updating the value in each sub-district row. This updated information forms the basis of the population estimation in the tsunami hazard model. Figure 3-10 shows an example of the attribute table with the updated figures. In each sub-district row (NAME_3), the values of population and area are completed.



Table

Phuket

OBJECTID *	Shape *	NAME_1	NAME_2	NAME_3	ENGTYPE_3	SubDist_Pop	Area_Sqm
1	Polygon	Phuket	Kathu	Kamala	Sub district	6898	18.839768
2	Polygon	Phuket	Kathu	Kathu	Sub district	28241	40.271837
3	Polygon	Phuket	Kathu	Pa Tong	Sub district	20628	19.185094
4	Polygon	Phuket	Muang Phuket	Chalong	Sub district	24733	26.020161
5	Polygon	Phuket	Muang Phuket	Ka Ron	Sub district	8147	22.408761
6	Polygon	Phuket	Muang Phuket	Ko Kaeo	Sub district	13984	24.87018
7	Polygon	Phuket	Muang Phuket	Ratsada	Sub district	46865	33.226548
8	Polygon	Phuket	Muang Phuket	Rawai	Sub district	17586	40.747263
9	Polygon	Phuket	Muang Phuket	Talat Nuea	Sub district	22314	3.232878
10	Polygon	Phuket	Muang Phuket	Talat Yai	Sub district	56609	5.229521
11	Polygon	Phuket	Muang Phuket	Wichit	Sub district	48628	37.712179
12	Polygon	Phuket	Thalang	Choeng Tale	Sub district	18275	29.773562
13	Polygon	Phuket	Thalang	Mai Khao	Sub district	13005	49.165419
14	Polygon	Phuket	Thalang	Pa Khlok	Sub district	15960	68.613472
15	Polygon	Phuket	Thalang	Sakhu	Sub district	6345	22.919789
16	Polygon	Phuket	Thalang	Si Sunthon	Sub district	23611	44.67259
17	Polygon	Phuket	Thalang	Thep Krasatti	Sub district	22340	67.521208

0 (0 out of 17 Selected)

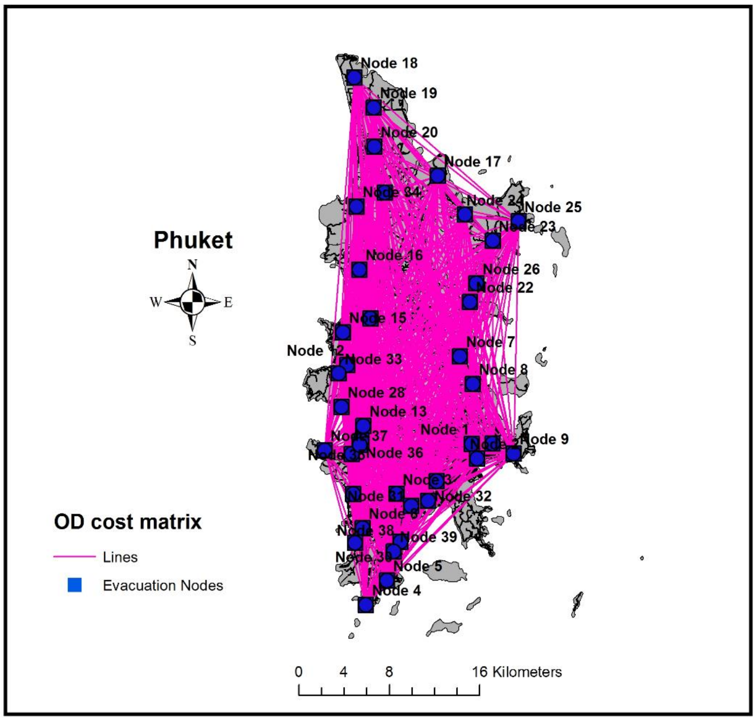
Phuket

Figure 3-10: Attribute database preparation.

3.4.1.4 Cost matrix preparation

The cost matrix finds and measures the paths that cost the least along the network from the origin to multiple destinations. This matrix data is an important input for solving the CVRP model. The destinations in this context are the evacuation locations specified in the study area, each of which contains a quantity of estimated demands.

By creating the cost matrix of all delivery nodes, the origin-destination cost matrix solver in ArcGIS Network Analyst was used to obtain the geographic output as illustrated in Figure 3-11, which describes the least-cost distances from the relief supply centre to the 38 nearest demand nodes. By opening the cost matrix's attribute table, the distance-matrix data then was exported in a spreadsheet template for use as input data in the CVRP optimisation.



Table

Lines

ObjectID	Shape	Name	OriginID	DestinationID	DestinationRank	Total_Kilometers
3121	Polyline	Node 1 - Node 1	41	79	1	0
3122	Polyline	Node 1 - Node 2	41	80	2	1.759849
3123	Polyline	Node 1 - Node 10	41	88	3	2.629132
3124	Polyline	Node 1 - Node 9	41	87	4	4.78863
3125	Polyline	Node 1 - Node 11	41	89	5	5.132478
3126	Polyline	Node 1 - Node 8	41	86	6	5.99524
3127	Polyline	Node 1 - Node 32	41	110	7	8.201736
3128	Polyline	Node 1 - Node 7	41	85	8	8.726445
3129	Polyline	Node 1 - Node 31	41	109	9	9.151324
3130	Polyline	Node 1 - Node 3	41	81	10	9.428908
3131	Polyline	Node 1 - Node 13	41	91	11	11.749829
3132	Polyline	Node 1 - Node 38	41	116	12	11.824008
3133	Polyline	Node 1 - Node 35	41	113	13	13.091493
3134	Polyline	Node 1 - Node 39	41	117	14	13.285413
3135	Polyline	Node 1 - Node 36	41	114	15	13.492358
3136	Polyline	Node 1 - Node 27	41	105	16	14.728848
3137	Polyline	Node 1 - Node 28	41	106	17	14.74373
3138	Polyline	Node 1 - Node 6	41	84	18	15.074599

1 (0 out of 1521 Selected)

Lines

Figure 3-11: Cost matrix preparation.

3.4.1.5 Tourist statistics preparation

In the tourist data provided by the DOT, the number of tourists who visited in 2016 were distributed by month on an average basis. Moreover, the specified tourist spots were approximately weighted based on historical visits. Subsequently, each evacuation node was specified as the location responsible for those living in the nearest tourist spot as illustrated in Figure 3-12.

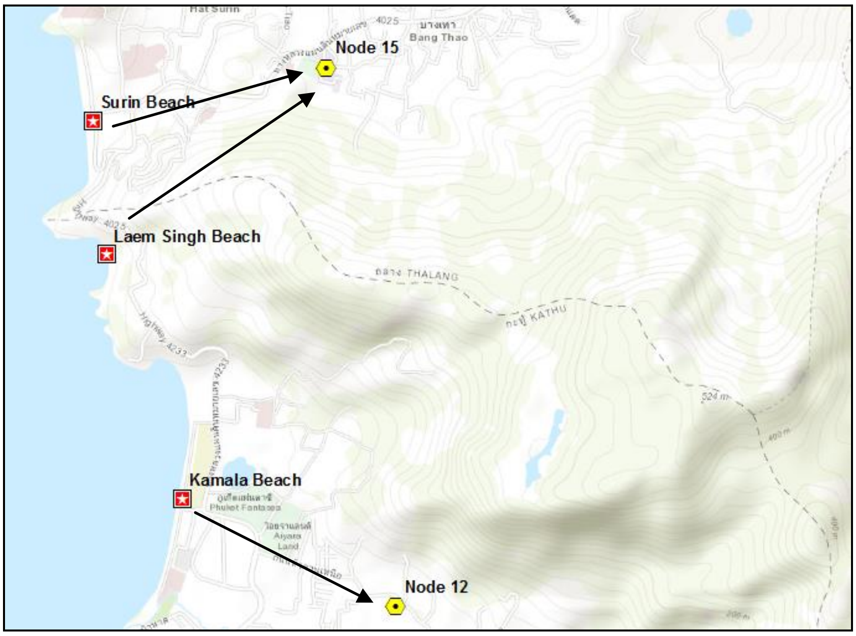


Figure 3-12: Evacuation node responsible to the nearest tourist spot.

As a result, each node had a tourist distribution by month throughout the year. This meant the mean and standard deviation of tourists for each evacuation location can be calculated as shown in Table 3-3. This statistical data was used in the randomised process to obtain the simulated population for tourists in the CVRP optimisation.

Evacuation node	Tourist spot	Mean	Standard deviation
3	Ao Chalong	434	102
4	Ao Sane	316	75
4	Nai Han Beach	1107	261
4	Ya Nui Beach	790	187
5	Rawai Beach	316	75
6	Kata Beach	1581	373
12	Kamala Beach	317	75
12	Lam Singh Beach	790	187
14	Bang Tao Beach	632	149
15	Pansea Beah	474	112
15	Surin Beach	632	149
20	Mai Khao Beach	316	75
21	Nai Yang Beach	790	187
25	Ao Po	1301	307
27	Freedom Beach	1440	340
29	Karon Beach	1880	444
30	Kata Noi Beach	1107	261
31	Ao Chalong	867	205
32	Ao Chalong	650	154
33	Kamala Beach	317	75
34	Nai Thon Beach	316	75
35	Patong Beach	711	168
36	Patong Beach	711	168
37	Paradise Beach	632	149

Table 3-3: Tourist statistical data assigned to evacuation node.

3.4.2 DSS development

As noted previously, the GIS-based DSS proposed in this research was developed using IntelliJ IDEA Community Edition, with Python and Java used to develop APE and HLO, respectively. The main purpose of the proposed DSS is to provide relief distribution plans by determining the least-cost vehicle routes with the transportation resources used to facilitate decision making in the aftermath of a tsunami disaster.

The outcomes are subject to a set of input data and parameters given by the user via user interfaces. The intuitive user interfaces are designed to clearly provide the area for inputting data and parameters, as well as the area for outputs in the same platform. In addition to seeing instant outcomes on the user interface, the user can visualise the solutions in the GIS environment to perform route analysis in the real-time response phase because the DSS can link its solutions to the ArcGIS platform.

3.4.2.1 DSS development framework

The GIS-based DSS was developed based on two study areas: the population estimation and CVRP optimisation. Basically, the two systems are connected as one platform; however, because the DSS is subject to a particular situation, each system can be operated separately.

The flow of decision-making using the DSS platform to obtain a route plan for humanitarian logistics is shown in Figure 3-13. The DSS platform adjusts the output based on the conditions applied such as when a tsunami strikes the study area, for example, during a specific time such as peak-hour day time during the high tourist period.

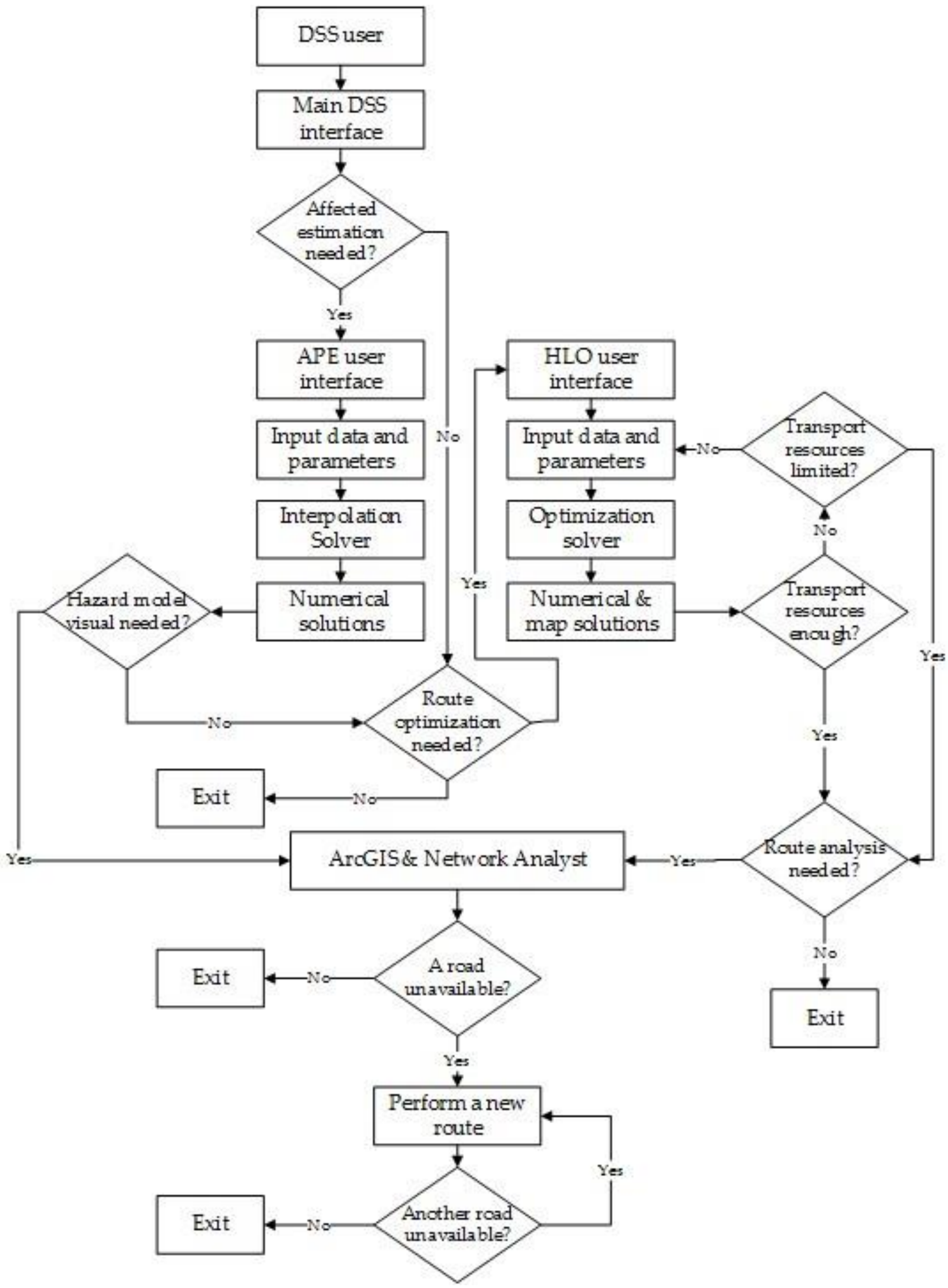


Figure 3-13: DSS framework.

3.4.2.2 DSS graphic user interface (GUI) design

To make the GIS-based DSS more user-friendly, navigation was considered as the most important aspect of the graphical user interfaces (GUIs). Thus, control elements (e.g. button, text box, list box) were added to the user interfaces. Each GUI contains a different pattern of entities, based on its function, to perform the data and parameter input. The main GUI of the proposed DSS is shown in Figure 3-14. This GUI simply includes two options to either perform the APE or HLO. Table 3-4 shows the control elements of the main GUI and their functions.

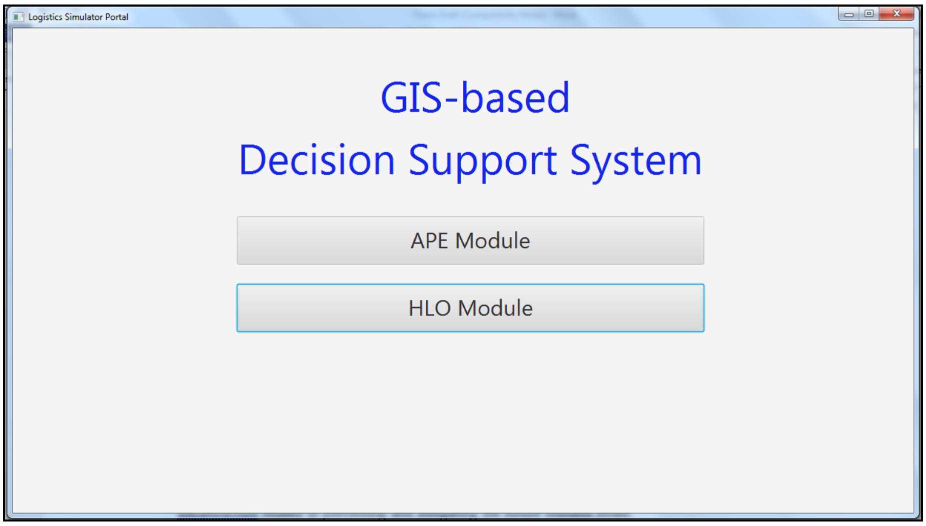


Figure 3-14: Main user interface design.

No.	Control element	Caption name	Data type	Function
1	Button	APE	-	To access APE environment
2	Button	HLO	-	To access HLO environment

Table 3-4: Control elements of the main GUI.

When accessing the APE, a subsystem of the DSS, a GUI pops up for the user to input the data and parameters. Figure 3-15 portrays the APE's user interface that is designed with different control elements, each of which is described in Table 3-5. The screen has two main partitions showing input and output elements. In addition to being displayed on the GUI, outcomes are generated in a spreadsheet for use as a data input for the HLO.

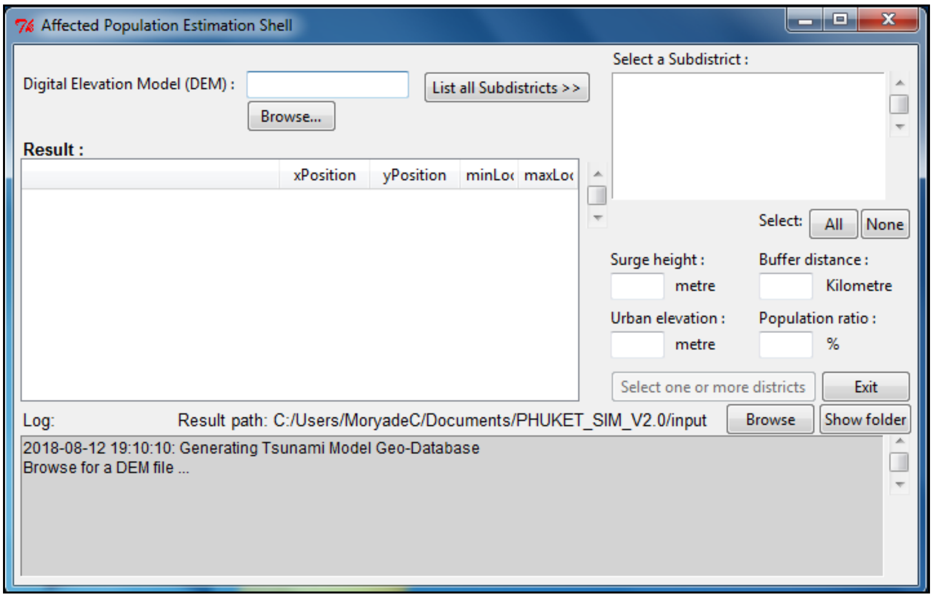


Figure 3-15: APE user interface design.

No.	Control element	Caption name	Data type	Function
1	Entry box	Digital Elevation Model (DEM)	Text	Receive the DEM input
2	Button	Browse	-	Browse for a DEM file
3	Button	List all Subdistricts	-	Extract sub-district from the area input
4	List box	Select a subdistrict	Text	View all sub-districts of the area input Allow user to choose an area/areas for estimating affected population
5	Button	All	-	Choose all sub-districts showing in the list box
6	Button	None	-	Undo the chosen
7	Entry box	Surge height	Double	Receive tsunami wave height
8	Entry box	Buffer distance	Double	Receive a distance away from the flood path that is considered to be affected
9	Entry box	Urban elevation	Double	Receive a value of terrain elevation that is considered where most people are settled
10	Entry box	Population ratio	Double	Receive a percentage that is considered to be people who live in the urban elevation
11	Button	Select one or more districts	-	Perform the estimation
12	Button	Exit	-	End and exit programme
13	Button	Browse	-	Select a folder to keep the result file
14	Button	Show the folder	-	Identify the folder for storing the result file
15	List box	Log	Text	Show the real-time programming status

Table 3-5: Control elements of the APE user interface.

With respect to the HLO user interface, there are three main partitions: data and parameters input section, numerical result division and map visualisation demonstration. The input section is subdivided into areas including transport resources entry, demand and location input, algorithm list, simulation round, seasonal parameters input and basemap for the visualisation display.

The output division is further divided into three subareas as shown in Figure 3-16. The main solution area shows the key results, including total cost, total demand served, number of routes generated and transport resource ratio.

Two other sections describe route priority in sequence and demand served in each evacuation node in each route.

Figure 3-16: HLO user interface design.

The map display can show both input data and geographical output. For example, the evacuation nodes can be shown on the map during the input stage. After performing the optimisation, the route solution can be displayed, enabling the user to visualise the solution on the study area map. In addition to the solution showed on the user interface, the shapefiles of all routes generated can be displayed and analysed in the ArcGIS platform, and further analysed by using Network Analyst. All control elements used to design the HLO user interface are illustrated in Table 3-6.

No.	Control element	Caption name	Data type	Function
1	Entry box	Number of vehicles	Integer	Receive a number of vehicles for use in the distribution
2	Entry box	Vehicle capacity	Integer	Receive the vehicle capacity that contains relief items
3	Entry box	Max. vehicle speed	Integer	Receive the maximum speed of the vehicle that are allowed in the operation
4	Entry box	Max. operation time	Integer	Receive the maximum time that is expected for finishing the operation (deadline)
5	Button	Browse	-	Browse for spreadsheet data input
6	Button	Show points on map	-	Show evacuation nodes on the map
7	List box	Select algorithm	Text	Choose an algorithm to solve the CVRP problem
8	Entry box	Round of demand simulation	Integer	Receive a number of rounds for simulating demand using the Monte Carlo technique
9	List box	Impact level	Text	Receive a level of impact for local residents
10	Button	Low	-	Low tourist season
11	Button	High	-	High tourist season
12	List box	Map configuration	Text	Choose type of basemap to be shown in the map-view section
13	Label	Total distance	Double	Show total cost in the solution
14	Label	Total demand	Integer	Show total demand served for all nodes
15	Label	Total nodes served	Integer	Show the number of nodes visited by the vehicle
16	Label	Number of routes generated	Integer	Show number of routes in the plan
17	Label	Resources used ratio	Double	Show the ratio of transport resources used
18	Button	Route List	Text	Show route priority and total demand served in each route
19	Button	Demand Serving List	Text	Show the quantity of demand served to each node
20	Option box	CSV	-	Choose to save route solution in the csv file format
21	Option box	SHP	-	Choose to save route solution in the shapefile format
22	Button	Optimise	-	Perform the problem

Table 3-6: Control elements of the HLO user interface.

3.5 Chapter Summary

This chapter described the research methodology. The research framework was motivated by the need to improve logistics mechanisms for assisting people affected by a tsunami. An attentive aspect of logistics was how to deliver relief items to evacuees stranded across affected areas in a timely manner with minimum resources. As a result, the population estimation using GIS technology and the CVRP algorithm were studied and developed as a spatial DSS that facilitates making decisions for planning and operating humanitarian logistics. Hence, the study encompasses three main phases: affected population estimation, CVRP optimisation and GIS-based DSS development.

Subsequently, the materials used in this research were described. In each study phase, a set of collected data were used to test a number of problem scenarios. In the DSS development phase, IntelliJ IDEA software was used to design and code computer languages according to the proposed algorithms. Another essential tool is ArcGIS 10.3 in which GIS data were prepared using the software's functionalities. The population estimation technique also was analytically operated in the ArcGIS environment. In addition, the Network Analyst extension in ArcGIS enabled the decision maker to do a re-routing to avoid damaged roads in a real-time situation.

With respect to the methods contributing to this research achievement, this chapter explained the data preparation which was important in gaining experimental results in each study phase. Then, development of the GIS-based DSS was described in terms of its conceptual framework and design. The appearance of the subsystems of the proposed DSS were illustrated.

Chapter 4: An Analysis of Pertinent Factors in the Case Study Area

4.1 Introduction

Phuket Island, Thailand serves as the study area for this research. It was chosen because it is in the Indian Ocean where active seismic faults exist. This means that earthquakes and subsequent tsunamis are likely to occur unpredictably. Moreover, it is an island and hence difficult to support in a disaster if the logistics are not well planed. Furthermore, as the island serves as one of the magnificent tourist spots in the world, the large number of seasonal tourists makes accurate logistics planning essential.

In 2004, Phuket was struck by the powerful tsunami triggered by an earthquake along a thrust fault in the subduction zone, where the Indian Ocean tectonic plate goes below the overriding Burmese plate. The moving of these two plates likely will cause a collision again in the future. Contributing to the tsunami risk factors in this area are the topographical characteristics of Phuket, particularly in low elevation areas along the coast. Thus, these coastal areas again could be exposed to critical damage due to a tsunami inundation.

Numerous coastal areas in Phuket were affected by the 2004 tsunami. The tsunami surge moved inland, destroying property and public infrastructure. The tsunami also affected local residents and visitors travelling on the island, which had no plans for tsunami warnings or evacuations. This resulted in many deaths and injuries. Consequently, relief logistics were unable to help the affected population.

The lessons learned from the 2004 event brought Thai authorities' attention to tsunami consequences. As a result, the coastal areas in the southern Thailand, including Phuket, were identified as a region exposed to tsunamis. The necessary infrastructure also was established (e.g. tsunami warning system, sign posting, and evacuation shelter) to cope with a future tsunami. For example, a warning system was settled in the region. In addition, evacuation procedures were planned such as evacuation routes and gathering points. Therefore, it is valuable to establish logistics plans for alleviating casualties based on the developed infrastructure.

For these reasons, this research takes Phuket as the case study for planning humanitarian logistics if a tsunami occurs in the future. The following sections explain the study area in terms of its geographic and demographic conditions, and how the 2004 tsunami affected it. Section 4.1 provides an introduction, followed by Section 4.2 with an overview of the geographic condition of the study area. Next, Section 4.3 provides the population data in the study area. Subsequently, Section 4.4 describes the 2004 tsunami impacts on the area. Then, the Thailand Master Plan for Tsunami Evacuation is briefly explained in Section 4.5. Finally, Section 4.6 gives a summary of the chapter.

4.2 Geography of Phuket

Phuket is an island situated on the southwest coast of Thailand. The island is 49 km long and 21 km wide, with a total area of 570 km^2. Phuket is separated from the mainland and located in the Andaman Sea, which is a part of the

Indian Ocean. It is the largest island in Thailand, and it is considered a province. About 70 percent of the area is mountainous with a mountain range on the west side of the island lying from north to south. The highest peak is Mai Tha Sip Song, or Twelve Canes, at 539 metres above sea level; it is in the boundaries of Patong and Kathu districts. The remaining 30 percent of the island, mainly in the centre and the south, is formed by low plains. The overall geography of Phuket is illustrated in Figure 4-1.

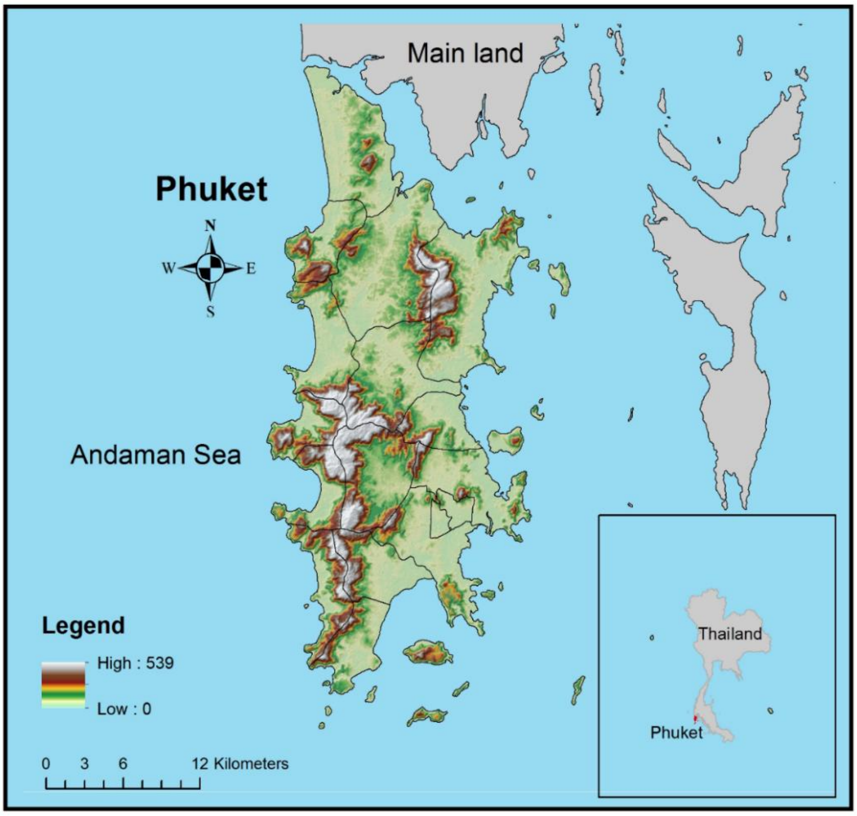


Figure 4-1: Overall geography of Phuket.

Furthermore, Phuket is Thailand's foremost tropical beach holiday destination. Several fine beaches line the west coast of the island. They have been forged by the waves from the Indian Ocean that beat into this side of the island through the rainy season, creating spectacular beaches in bays split by rocky headlands as shown in Figure 4-2.

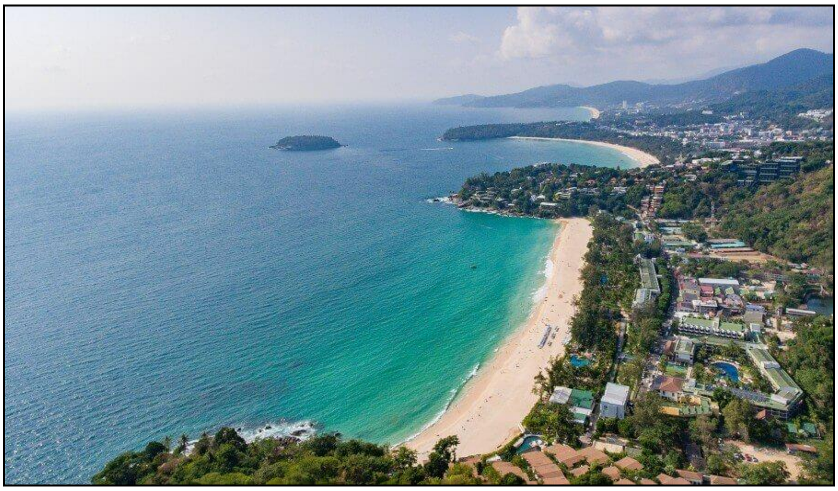


Figure 4-2: Geographic condition along the west coast of Phuket.

The east coast of the island has smaller beaches that tend to be a little muddy. This is because the seabed on the sheltered east coast still has a lot of sludge and mud stirred up from the old tin-mining days when the seabed was extensively dredged. For this reason, much of the east coast is covered by mangrove forest, as shown in Figure 4-3. That side of the island attracts tourists, however, because there is a major pier, Ao Po, which is one of the main gateways for exploring other islands in the Andaman Sea.

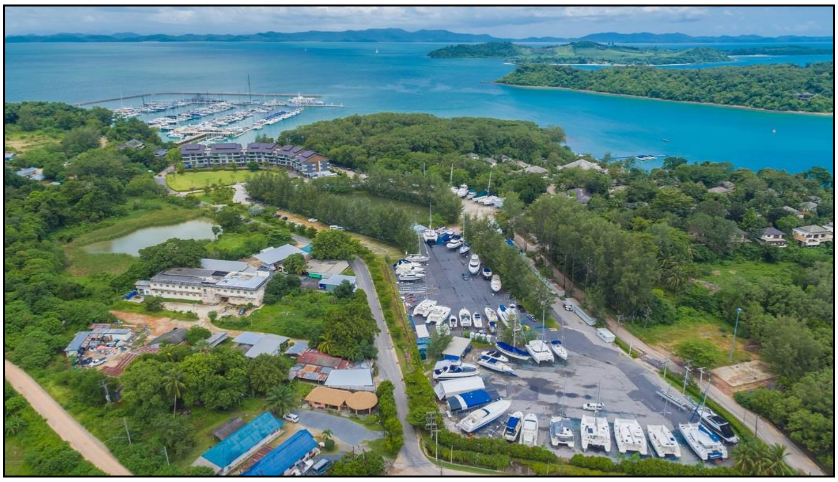


Figure 4-3: Geographic condition along the east coast of Phuket.

Due to its magnificent seashores, old towns and hillsides, Phuket is one of the world's top tourist spots, attracting both domestic and international vacationers. The most popular tourist area in Phuket is Patong Beach on the central west coast, perhaps owing to the easy access to its wide and long beach. Also, most of Phuket's nightlife and its shopping centres are in Patong, and the area has become increasingly developed. In addition to Patong, Phuket has other magnificent attractions as illustrated in Figure 4-4.

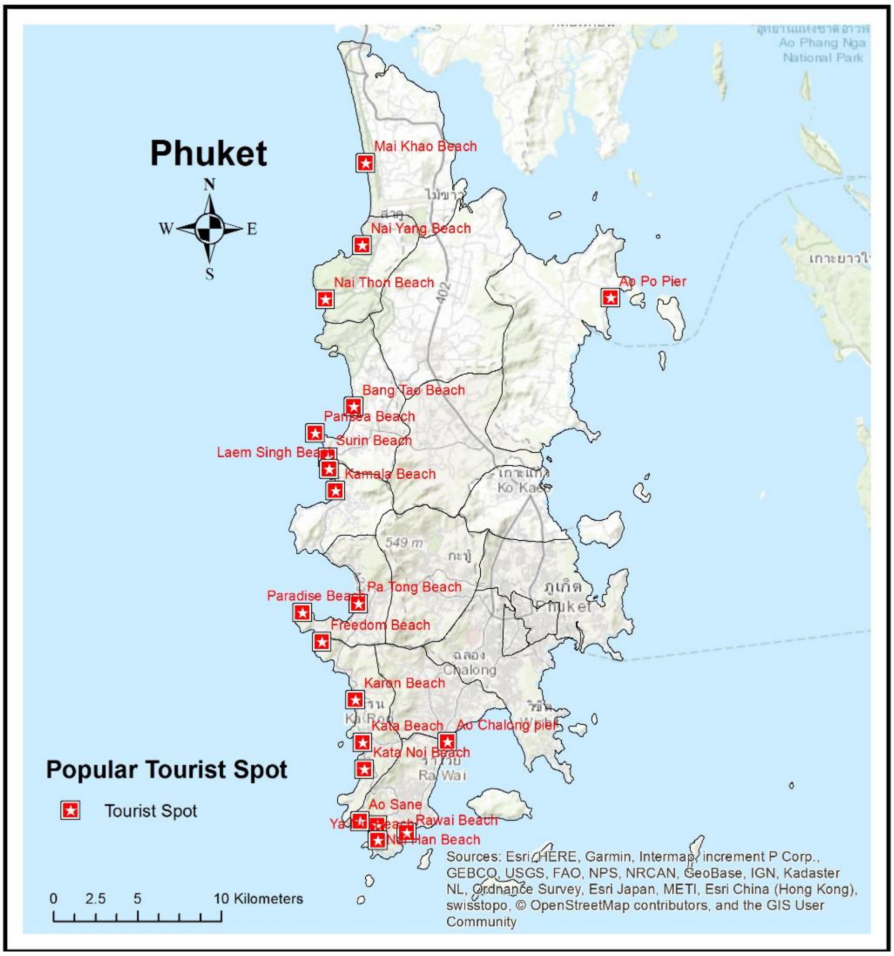


Figure 4-4: Phuket attractions map.

4.3 Population of Phuket

The study area of this research covers three districts which are further subdivided into 17 sub-districts. The official population of Phuket is approximately 394,169 people but this only includes those registered as permanent residents. The Phuket provincial population in 2016 was registered at about 365,938 people, according to the Department of Provincial Administration (DOPA), Ministry of Interior, Thailand. Table 4-1 shows the population as divided in each sub-district.

District	Sub-district	Population
Kathu	Kathu	28,241
	Kamala	6,898
	Patong	20,628
Thalang	Pa Khlok	15,960
	Choeng Tale	18,275
	Thep Kasatti	22,340
	Mai Khao	13,005
	Sakhu	6,345
	Si Sunthon	23,611
Meaung Phuket	Karon	8,147
	Wichit	48,628
	Chalong	24,733
	Ratsada	46,865
	Ko Kaew	13,984
	Rawai	17,586
	Talat Yai	56,609
	Talat Nuea	22,314
Total population		394,169

Table 4-1: Phuket population (updated in 2016).

Source: DOPA, Ministry of Interior, Thailand

Figure 4-5 shows that the main population centre is Meaung Phuket. Other main population areas are the coastal towns along the west coast such as Patong, Karon, Kamala, and Choeng Tale.

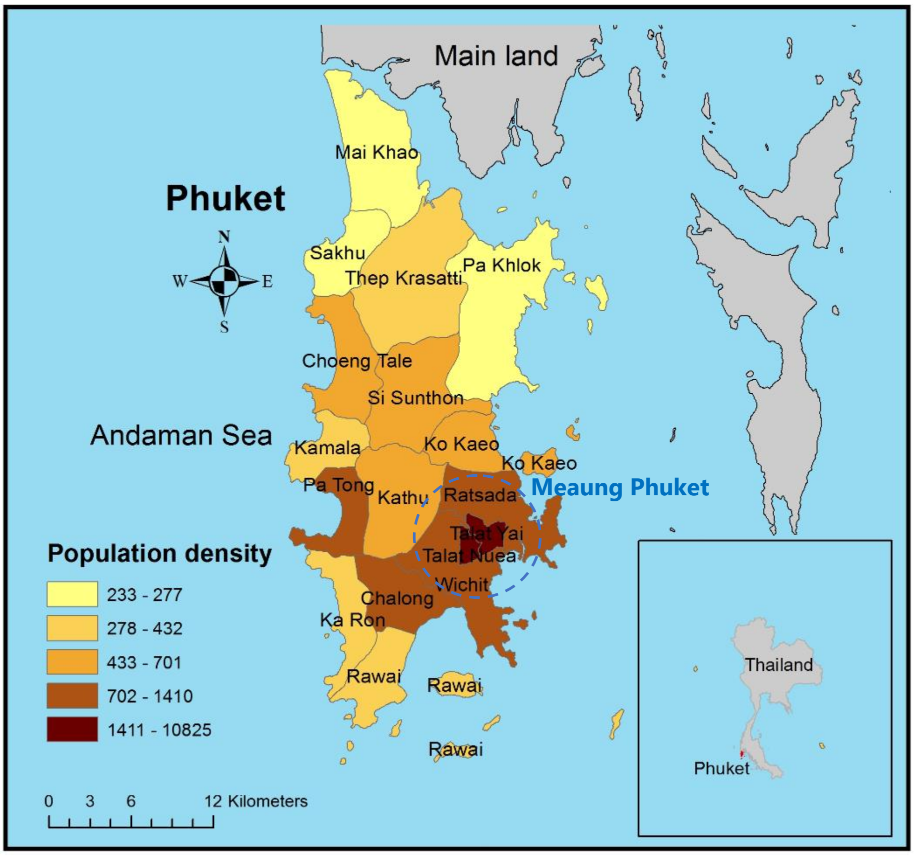


Figure 4-5: Sub-districts in Phuket.

In addition to registered inhabitants, there is a dynamic population travelling in and out of the area throughout the year for vacations. The number of people on Phuket Island swells to more than one million during the high season, as tourists, mainly from Western Europe, China, Britain and the United States, visit the island. Table 4-2 presents the number of tourists, both domestic and international, who visited Phuket between 2009 and 2016, according to the Department of Tourism (DOT), Ministry of Tourism and Sports, Thailand.

Year	Domestic	International	Total (People)
2009	887,365	2,488,566	3,375,931
2010	965,192	4,506,026	5,471,218
2011	2,844,472	6,622,776	9,467,248
2012	2,643,541	6,185,757	8,829,298
2013	3,564,123	8,395,921	11,960,044
2014	3,499,187	8,459,416	11,958,603
2015	3,714,328	9,488,956	13,203,284
2016	3,845,532	9,495,697	13,341,229

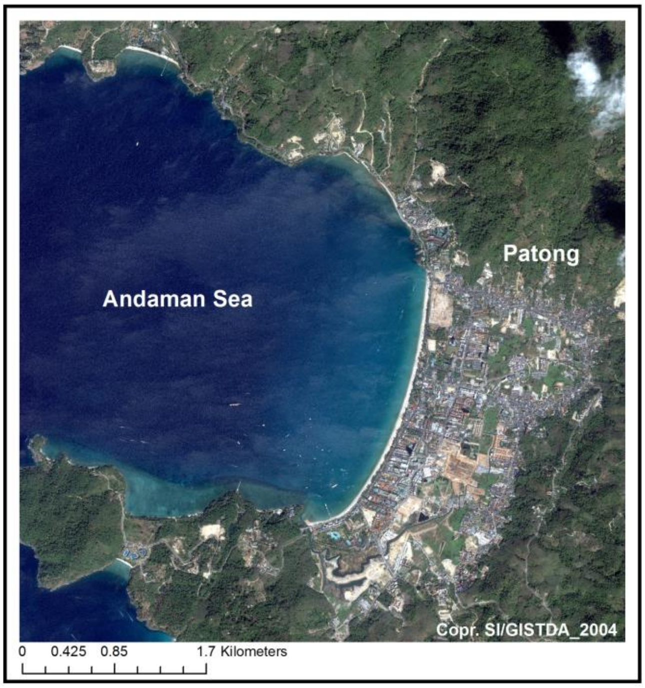
Table 4-2: Statistics of tourists visiting Phuket between 2009 and 2016.

Source: DOT, Ministry of Tourism and Sports, Thailand

According to Table 4-2, the number of visitors travelling in Phuket each year is far greater than those permanently living in the area. Hence, it is necessary to consider tourist figures in estimating a snapshot of the population in the study area to obtain an accurate solution for this study.

4.4 The Impacts of the 2004 Tsunami in Phuket

On 26 December 2004, a 9.3-magnitude earthquake struck deep under the Indian Ocean off the west coast of Sumatra, Indonesia, triggering the tsunami that slammed the Andaman coastal provinces in southern Thailand. The incident affected six provinces, including Phuket, Trang, Phang Nga, Krabi, Ranong and Satun, which can be further divided into 25 districts, 95 tambons (sub-districts) and 407 villages. To illustrate the area affected by the tsunami, Figure 4-6 shows the Patong area on 24 December 2004, before the tsunami (4-6a), and on 28 December 2004, after the tsunami (4-6b), as captured by the Landsat satellite. The satellite images are provided by Geo-Informatics and Space Technology Development Agency (GISTDA), Thailand.



(a)

(b)

Figure 4-6: Patong area before and after the 2004 tsunami occurrence.

Source: GISTDA, Thailand

4.4.1 Impact on human casualties

According to data reported by the Department of Disaster Prevention and Mitigation (DDPM), Ministry of Interior, Thailand, life loss in Thailand reached 5,388 people. Many of the unidentified persons are believed to be foreign tourists. The casualty statistics by province are shown in Table 4-3.

No.	Province	Number of deaths				Number of injured
		Thai	Foreigner	Unknown	Total	
1	Phang Nga	1,149	1,633	1,435	4,217	5,597
2	Krabi	349	198	174	721	1,376
3	Phuket	151	111	17	279	1,111
4	Ranong	156	11	-	167	246
5	Trang	3	2	-	5	112
6	Satun	6	-	-	6	15
	Total	**1,814**	**1,955**	**1,626**	**5,395**	**8,457**

Table 4-3: The number of affected people.

Source: DDPM, Ministry of Interior, Thailand

These data reveal a very high proportion of foreign nationals died because of the disaster. There is no doubt that this is because of the large number of foreigners that visit the resorts and hotels located in the affected area.

When the number of households and people directly affected by a loss of assets is considered, Table 4-4 reveals a similar pattern to Table 4-3 in that those most affected were in the provinces of Phang Nga, Krabi and Phuket.

No.	Province	Number of directly affected	
		Persons	**Households**
1	Phang Nga	19,509	4,394
2	Krabi	15,812	2,759
3	Phuket	13,065	2,616
4	Ranong	5,942	1,509
5	Trang	1,302	1,123
6	Satun	2,920	414
	Total	**58,550**	**12,815**

Table 4-4: The number of directly affected persons and households.

Source: DDPM, Ministry of Interior, Thailand

4.4.2 Impact on beachfront areas

The Indian Ocean tsunami that attacked southern Thailand was the most destructive natural disaster in the country's history (Chanditthawong, 2005). Severely impacted were the islands and mainland beaches of Thailand's coastal areas which faced the tsunami source. Especially hard hit was Phuket. When the tsunami struck Phuket, all its major beaches such as Patong, Karon, Kata and Kamala were suddenly affected.

In Phuket, the most affected area was along the beaches on the west side of the island when the waves from the Andaman Sea hit the shore. Beach structures, mainly constructed with bamboo and timber with lightweight roofs of steel sheeting and thatches, were wiped out as the waves advanced into the terrain, continuing on to the higher ground. The wave brought with it pebbles, sand, mud, broken debris, tree trunks and other unsecured objects such as boats, heavy steel tanks, motor cars, motorcycles and other rubble. These objects, large and small, were flushed through the narrow streets, destroying the ground floors of buildings as the waves passed through as shown in Figure 4-7.

Figure 4-7: Tsunami impact on Patong Beach, Phuket.

Source: Oberle, 2005

Moreover, many poorly constructed single-story buildings caved in and were washed away. Most shop fronts on the ground floor were wiped out. Hotels and department stores on the sea front suffered heavily on their ground floors and in basements where many dead victims were found after the waves subsided.

4.4.3 Impact on transportation networks

With respect to the transportation networks, there was no serious damage to the main major roads in Phuket. Minor damage to road surfaces was observed, however, in areas near the coastline (Saatcioglu *et al*., 2005). This was visible on small areas of roads adjacent to the beachfront and especially on grass-concrete surfaces, e.g. in Kamala and Patong.

Minor flooding was reported on the runway at Phuket International Airport. The airport was closed for several hours, however, due to high levels of sand and dust blown up by the main wave. No significant damage was reported to the runway and buildings, although part of the lighting system was temporarily affected (Pomonis *et al*., 2006). The airport was re-opened two days after the tsunami when flights arrived from Bangkok with aid workers who assisted in the early stages of the rescue and clean-up efforts.

4.4.4 Impact on water and electricity supply

There was no serious long-term disruption to the water and electricity supply in Phuket. The supply of electricity to inundated areas of Phuket was suspended for 2–3 days. Moreover, some damage to drainage pipes was observed at Patong Beach (Pomonis *et al*., 2006).

4.4.5 Impact on tourism industry

The DOT released the following summary table of data concerning the hotel capacity in Phuket, Phang Nga and Krabi, which were the worst-affected provinces. Table 4-5 shows the statistics of hotel damage in the three worst-affected areas.

In terms of economic losses due to tourism damage, the DOT reported that the provinces of Phuket, Phang Nga and Krabi were expected before the disaster to generate 3 billion US$ worth of tourism income to the Thai economy, but in the first month after the tsunami, tourist arrivals were down 88% compared to the previous year.

Province	No. of Operational hotels	% of Operational hotels	No. of Operational rooms	% of Operational rooms	No. of hotels before tsunami	No. of rooms before tsunami	Damaged hotels
Phuket	472	82.4%	26,726	83.3%	573	32,585	101
Phang Nga	46	32.2%	1,098	19.8%	143	5,533	97
Krabi	292	83.2%	9,042	77.2%	351	11,709	59
Total	**810**	**75.9%**	**36,902**	**74.1%**	**1,067**	**49,827**	**257**

Table 4-5: Statistics of the hotels damaged by the 2004 tsunami.

Source: DOT, Ministry of Tourism and Sports, Thailand

4.4.6 Relief effort responded to the tsunami impact

With respect to the relief effort, according to DPM (2005), the Thai government provided relief to help the high-end resorts in Phuket recover because tourism is one of the country's largest industries. One of the most notable aspects of the tsunami was the efforts of the Thai people who banded together to provide aid to tourists affected by the tsunami in Phuket. The disaster hit tourist-dense areas like Patong hard, with much of the hotel and entertainment structures affected. A few years later, European governments provided funding for Phuket to rebuild the Patong area, which has resulted in a more aesthetically pleasing district.

4.5 Thailand Tsunami Master Plan

In 2005, the Thai government issued a master plan for tsunami evacuation particularly focusing on the west coastal fringe of Thailand, which was identified as a tsunami-prone area. The document highlights three phases of tsunami evacuation: pre-disaster, during the disaster, and post-disaster that follows Carter's (1999) approach. Figure 4-8 shows the activities identified in each phase.

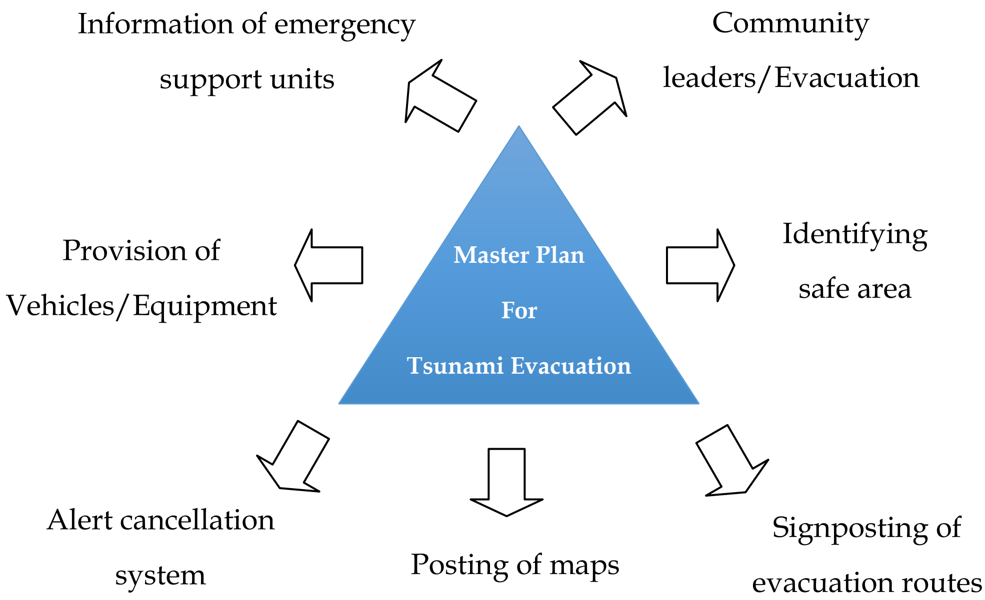


Figure 4-8: Master plan for the tsunami evacuation.

Source: DPM, 2005

Interestingly, the master plan and response facilities were tested by the earthquakes, which occurred at the same location as the 2004 case. The warning facilities (e.g. warning siren) were utilized in this event. Some issues found in the 2012 tsunami case event are discussed below.

On 11 April 2012, at about 15:40 local time in Thailand, there was an earthquake with a magnitude of 8.6 at almost the same location as the 2004 earthquake. The Thailand response mechanism started issuing an official warning siren around 5 minutes after the tremor. As a result, the evacuation process began although there was no following tsunami.

According to Tatham and Christopher (2014), some specific problems with regards to the tsunami warning experiences in 2012 are mentioned below;

- Inconsistent evacuation route signage – the signage was inconsistent in terms of clarity and prominence, e.g. there was no sign at the critical location.
- No special arrangements for the elderly/infant/disabled – this led to chaos and frustration among evacuees.
- Lack of basic facilities at the refuge – the evacuees had to stay for 4 hours without facilities, drink, and food.
- No information tools at the refuge – this also led to no information updates and a greater filtering of information was needed to establish facts during the emergency warning period.
- Human behaviour variations – the way evacuees behave in an emergency situation that can lead to survival or loss of human life.

Therefore, it can be said that there still were obvious problems in the response phase of the 2012 tsunami warning case. According to the field researchers experiencing the 2012 case event, there is a compelling need to improve the humanitarian response, and the best way to achieve this in the future is to be better prepared by having response structures in place and to act appropriately after an emergency warning is triggered (Tatham and Christopher, 2014).

4.6 Chapter Summary

This chapter describes the characteristics of the case study area in several aspects. The main purpose for choosing Phuket as the area to study is because its location is directly in the path of a potential tsunami. Also, Phuket is an important province in Thailand that can contribute to the economy due to the tourism industry. This provincial island is one of the world's top tourist destinations due to its very fine beaches and blue sea, as well as hillsides that attract people from around the world.

Moreover, there has been an increase in population figures in Phuket every year, among both local residents and travellers. The more tourists visit Phuket, the more residents move their property, mainly commercial buildings, close to the seafront areas for business reasons. Thus, more and more people are living and travelling in the hazard areas and could be categorised as vulnerable people for tsunami inundation.

The 2004 tsunami affected Phuket on many fronts such as casualties, infrastructure, and local industries. As an immediate consequence, it damaged infrastructure such as transportation networks, water supply and electricity supply with numerous casualties who were unable to receive relief efforts in a timely manner. Thus, a tsunami prevention and mitigation plan, as well as a relief logistics plan, must be well prepared in case of such a circumstance recurring in this region.

Following the 2004 event, the Thai government established a master plan to deal with a tsunami. The plan includes acquiring tsunami warning systems along the hazard areas. Also, evacuation routes and gathering points have been established. Hence, the structures for coping with tsunamis already have been settled in Phuket, making the island suitable for use as the case study in this research.

Chapter 5: A Method for Tsunami Affected Population Estimation

5.1 Introduction

On December 26, 2004, a 9.3-magnitude earthquake and the following tsunamis in the Indian Ocean stimulated interest in disaster relief and demonstrated the vulnerability of coastal areas with distributed populations, which required more efficient humanitarian relief efforts. In the south of Thailand, one of the affected areas, the delivery of humanitarian aid was stated as a major problem in the aftermath of the tsunami (Banomyong *et al*., 2009). The lesson learnt from this 2004 Thailand disaster was that the tsunami-devastated urban areas, with their unplanned evacuation points, and perhaps most importantly, the failure to estimate the affected population after the onset of the disaster, led to unknown demand. In turn, this led to a deficiency in optimised-routing decisions, resulting in insufficient, misdirected, and delayed relief logistics operations.

As 80 per cent of disaster relief involves logistics activities, humanitarian logistics must be acknowledged as a crucial factor in disaster relief operations (Kovács and Spens, 2007; Van Wassenhove, 2006). In the humanitarian field, allocating supply items to the people affected by disasters can be a matter of life and death, and it is significantly different from those served to customers in the business environment. Therefore, basic survival needs must be systematically delivered as quickly as possible once a disaster occurs. As this can be a large and urgent need, applying optimisation techniques for vehicle routing to facilitate humanitarian logistics is critical for reaching survivors. Hence, due to the criticism of the tsunami response in Thailand, there is a compelling need to improve humanitarian relief logistics in tsunami-prone areas, and the best way to achieve this in the future is to be better prepared for relief routing and scheduling.

However, the characteristics of these humanitarian logistics involve high uncertainties in many aspects such as the locations and affected numbers. Decision makers, therefore, prevalently face some specific challenges, especially in obtaining victim figures, which are directly proportional to demand in the delivery stage. Many scholars agree that good knowledge of demographic data can contribute to good planning (e.g. Hirschman, 1981, Keyfitz, 1993). Nevertheless, disasters rarely have respect for the administrative or political boundaries for which official population data are collected (Wood, 1994). As a result, assessing the population in the affected areas is difficult, as population data are mostly not tabulated for small areas such as census blocks, particularly in developing countries. This leads to difficulty in approximating the affected population, on which humanitarian logistics heavily depend. Yet population data alone is not sufficient to form effective humanitarian responses, as it should be accompanied by the availability of geographic data (National Research Council, 2007). Thus, the integration of population estimation methods into Geographic Information Systems (GIS) can be a powerful tool for manipulating disaster relief.

With regard to tsunami disasters, there are numerous associations researching and developing approaches using GIS to model tsunami inundation all over the world. However, it appears in the scientific literature that there is a limited amount of research on applying GIS to estimate the affected numbers in tsunami vulnerability areas. This chapter therefore proposes a GIS-based application to model a tsunami prone-area in the ArcGIS environment. It aims to apply areal interpolation techniques to estimate a range of affected population in each evacuation location in the small areas affected by tsunami inundation. This GIS-based approach provides not only numerical results but also alternative visualisation mapping so that decision makers can use such solutions for more efficient humanitarian relief logistics in the affected area.

5.2 Literature Review

More efforts to improve disaster relief are required from humanitarian organisations following the major disasters that have occurred across the world, e.g. the earthquakes and following tsunamis in the Indian Ocean in 2004 and in Japan in 2011, as well as the earthquakes in Pakistan in 2005 and Haiti in 2010 (Leiras *et al.*, 2014). As a result, risk and vulnerability models for natural disasters have received much attention in the humanitarian sector. When a disaster occurs, estimations of the affected numbers are needed to better plan for the humanitarian response, especially the relief logistics aspect (National Research Council, 2007; Jordan *et al.*, 2012). Therefore, a review of the literature on population estimation methods is an important stepping stone in developing good estimates of the disaster-affected population.

Over the last two decades, population estimation methods have mostly been found in the GIS and remote sensing literature. These methods fall into two groups: areal interpolation and statistical modelling. Areal interpolation is the transformation of known values in a set of source polygons to a set of target polygons in which the values of the variables are estimated (Hawley and Moellering, 2005). Specifically, this approach describes the interpolating of census population data in the source zone to obtain a population estimation for the target zone. Wu *et al*. (2005) separated areal interpolation methods into two categories: areal interpolation with and without ancillary information. Areal interpolation methods without ancillary information aggregate population data from a source zone for a population estimation for a target zone without any assisting data sources. Moreover, areal interpolation without ancillary information is further divided into point-based and area-based techniques (Lam, 1983). Point-based interpolation refers to a process of estimating unknown values that are distributed around a centroid point with a known value. In the population context, a centroid point represents a known population size of each source zone in which the population is uniformly distributed. In contrast, an area-based approach uses the entire volume of the source zone instead of a centroid point. A source zone and a target zone are overlaid to obtain a proportion that is used as a weight to estimate the population in the target zone. However, an area-weighting method is stated as an over-simplified assumption that the population in each source zone is uniformly distributed, which does not make sense in terms of human settlement (Kim and Yao, 2010). However, this weakness was improved by pycnophylactic interpolation, which was developed by Tobler (1979). The smooth density algorithm is used in Tobler's (1979) method to blend the boundaries between the zones, while having volume preservation for each zone (Kim and Yao, 2010; Tapp, 2010; Wu *et al*., 2005). The disadvantage of the pycnophylactic interpolation method, however, is that the population distribution can be distorted due to a lack of assisting information (Kim and Yao, 2010).

On the other hand, areal interpolation with ancillary information, also known as the dasymetric-mapping method, refers to a population estimation for which census population data are combined with other population-relevant variables such as building, land use, and transportation networks that can be used to suggest the most-likely population distribution. Although dasymetric-mapping is a promising approach for identifying populated zones, it has the inherent shortcoming of assuming a uniform distribution of the population in residential areas (Kim and Yao, 2010; Wu *et al*., 2005).

With respect to a statistical modelling approach, in contrast to areal interpolation methods, this approach employs statistical methods for estimating the total population size in an area to study the relationship between population and socioeconomic variables such as urban areas, land use, and dwelling units (Wu *et al*., 2005). For example, Lo and Wrech (1977) and Lo (2002) used this approach to study the relationship between population and urban areas to estimate the population size of many cities in the world. Lo and Chan (1980) and Lo (1989) estimated the total population in cities by observing dwelling units from aerial photographs. However, all studies using this approach are less accurate than those using areal interpolation techniques, particularly in small-area population estimation (Wu *et al*., 2005).

As a result, areal interpolation methods have been widely used and have received more attention in population-estimation research. For instance, Tobler (1979), Martin, (1996), and Rase (2001) studied and applied spatial interpolation without ancillary information techniques to obtain aggregate counts of population as well as population densities for many areas across the world. However, this approach encounters some significant problems, and the worst scenario is that the population estimation for the target zones does not give a valid overall sum of the source units (Wu *et al*., 2005). For research using the dasymetric-mapping method, Holt *et al*. (2004), Mennis (2003), Eicher and Brewer (2001) and Yuan *et al.* (1997) classified land use by transferring census population data in source units for redistributed populations in the target zones based on the types of land use. Due to the support of other data sources for interpolation, Wu *et al*. (2005) insisted that the methods using ancillary information usually produce more accurate results than those using only census population data. For example, Schmid-Neset *et al.* (2008) used transportation networks as the primary indicators of population, because roads and streets play a vital role in human settlement. More specifically, people actually tend to live and travel around street networks through their environments rather than in random spaces. Moreover, Reibel and Bufalino (2005) examined the street-weighted interpolation, which is the dasymetric-mapping, and the area-based technique for population estimation in the Los Angeles area. The street-weighted method shows better performance in terms of error reduction and ease of use compared to the area-weighted approach. However, Kim and Yao (2010) argued that the accuracy of population estimation can be improved by integrating the dasymetric-mapping method with area-based interpolation. In this sense, it would be more meaningful to develop a combination of interpolation techniques as suggestive of the population estimation in a specific area.

Not surprisingly, all the above population estimation techniques have been employed by cross-disciplinary researchers. Nevertheless, there are very few studies on population estimation with respect to natural disasters. Within this number, research on estimating disaster-affected populations is mostly found in the GIS and remote sensing literature. With the growth of GIS and remote sensing technologies, they have been increasingly used for assessing vulnerability models as well as estimating the affected numbers for many types of natural hazards. For example, Albert *et al*. (2012) studied a wide range of spatial techniques for estimating the population affected by disasters and came up with the conclusion that the best choice was the Population Explorer. This is a web-based application that presents the population data for the world with easy-to-use mapping and visualising tools. The Population Explorer has been used as a guide for initiating aid deliveries by using LandScan (global population distribution data) to estimate the local population of disaster-affected areas for users (Jordan *et al.*, 2012). Although the Population Explorer covers global population data with very fine resolution (0.5-meter resolution), it has some shortcomings. For example, using the application may be costly, as it is for commercial use only. Additionally, the census data are updated yearly, and thus, dynamic populations during a year may not be taken into account.

Furthermore, Gorokhovich and Doocy (2012) studied geographic vulnerability models for Typhoon Ketsana by using GIS coupled with pre-disaster population data to estimate the affected population. Cyclone vulnerable areas were visualised by combining data from surge and flood prone areas. The estimation of the affected population was produced by placing two layers of vulnerability models and spatially-distributed population data from the Global Rural Urban Mapping Project. The key variables in their models encompass terrain features, population density, and storm impact. However, their models produced estimates of the affected population in administrative boundaries in terms of provincial areas, and therefore, the subareas are not considered in their models.

For other studies, Ranjbar *et al.* (2017) estimated earthquake casualties using a GIS-based approach based on the immediate extraction of damaged buildings. Doocy *et al.* (2007) assessed tsunami mortality using GIS-based vulnerability models and demographic methods from surveys of tsunami-displaced populations. Balk *et al*. (2005) studied the estimation of coastal populations exposed to the 2004 tsunami by creating buffers of 1 and 2 km from the coast lines as vulnerability areas and using population data from the Global Rural-Urban Mapping Project (GRUMP).

As reviewed in the literature, GIS and remote sensing data have often been used in spatial data analyses for the purpose of estimating the disaster-affected population. Therefore, in this chapter, a GIS-based methodology is proposed to model a tsunami flood in a small area followed by an estimation of the local affected population. The algorithms of the population estimation are chosen from the discussions across the literature, resulting in the application of the concept of dasymetric-mapping methods for interpolation in the GIS environment.

5.3 Study Area and Dataset

In the south of Thailand, the 2004 tsunami was stimulated by the Indonesia earthquake and hit the Andaman coastal areas, destroying villages and infrastructure, and resulting in a large number of injuries and deaths. There were six coastal provinces affected by that disaster event (Phuket, Phang Nga, Krabi, Ranong, Trang and Satun).

Phuket is a provincial island, and it is relatively small but was the most densely populated region among the provinces affected by the 2004 tsunami. This area is one of the largest city economies in Thailand. Phuket is divided into three districts which are further subdivided into 17 sub-districts and 103 villages. Patong, a sub-district on the west coast of Phuket, was selected as the study area because it is a town in which a majority of commercial buildings and offices, residential units, and other social and service facilities are located near the shore line. This area has a range of mountains in the east lying from the north to the south as shown in Figure 5-1. Patong covers an area of about 19 square kilometres with a population of 20,628 (Thai Department of Provincial Administration, DOPA, updated in 2016). This town lies in the tsunami-prone area that was one of the worst affected areas on Phuket in 2004. Its position directly faces the Indian Ocean, where a number of massive undersea plates are moving at a regular rate over time, which can cause unpredictable plate collisions. Consequently, there is a high possibility that earthquakes and subsequent tsunamis will hit this area in the future. Figure 5-1 illustrates the Patong sub-district and the sample of datasets used in the case study.

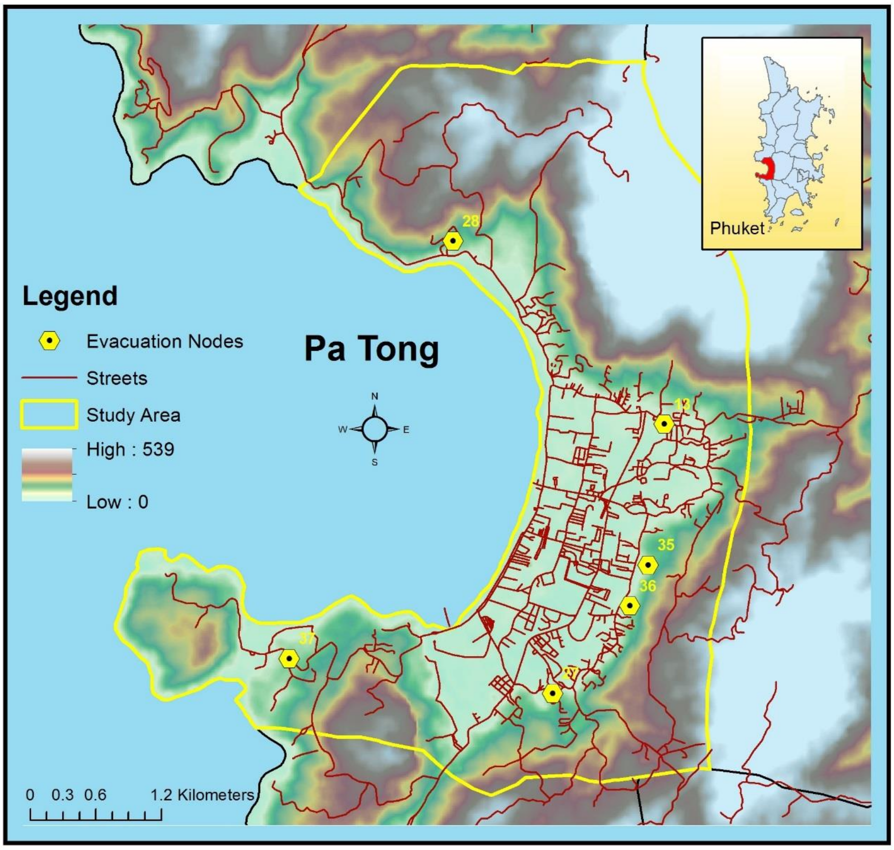


Figure 5-1: Study area in Phuket, Thailand.

All the data used in this case study are assessed using ArcGIS 10.3 software. Thus, the ArcGIS platform is also an essential component for the data preparation as well as further spatial analysis and geoprocessing operations. However, for such processes, an implementation of Python scripting in ArcGIS enables users to obtain results via the Graphic User Interface (GUI) without the need for analytical-operation skills in the GIS environment.

5.4 Methodology

This proposed method involves estimating the population exposed to a tsunami impact, and therefore, the affected people in this context must first be identified. The description of the affected people would be best defined by the EM-DAT database cited in Menoni and Margottini (2011) as the "people requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, sanitation and medical assistance, including those displaced or evacuated". This research thus uses this term for the affected people in all sections.

However, the affected people term here is divided into two categories: directly and indirectly affected. The directly affected population includes the people who live within the path of the flooding and receive the direct impact of the tsunami, such as injuries and the destruction of their properties and facilities, and who have essential needs. While indirectly affected people include those living outside the flooding path, the disaster may impact their medical and social services, or any necessary resource for living. Therefore, in this chapter, an estimation of the population affected in each area is given as a range of the minimum and maximum affected population. Direct flooding-affected refers to the minimum number, whereas the maximum is the sum of the directly and indirectly affected population. Figure 5-2 shows the overall process of estimating the affected population which consists of two main parts; data preparation and the tsunami hazard assessment and estimates of the affected population.

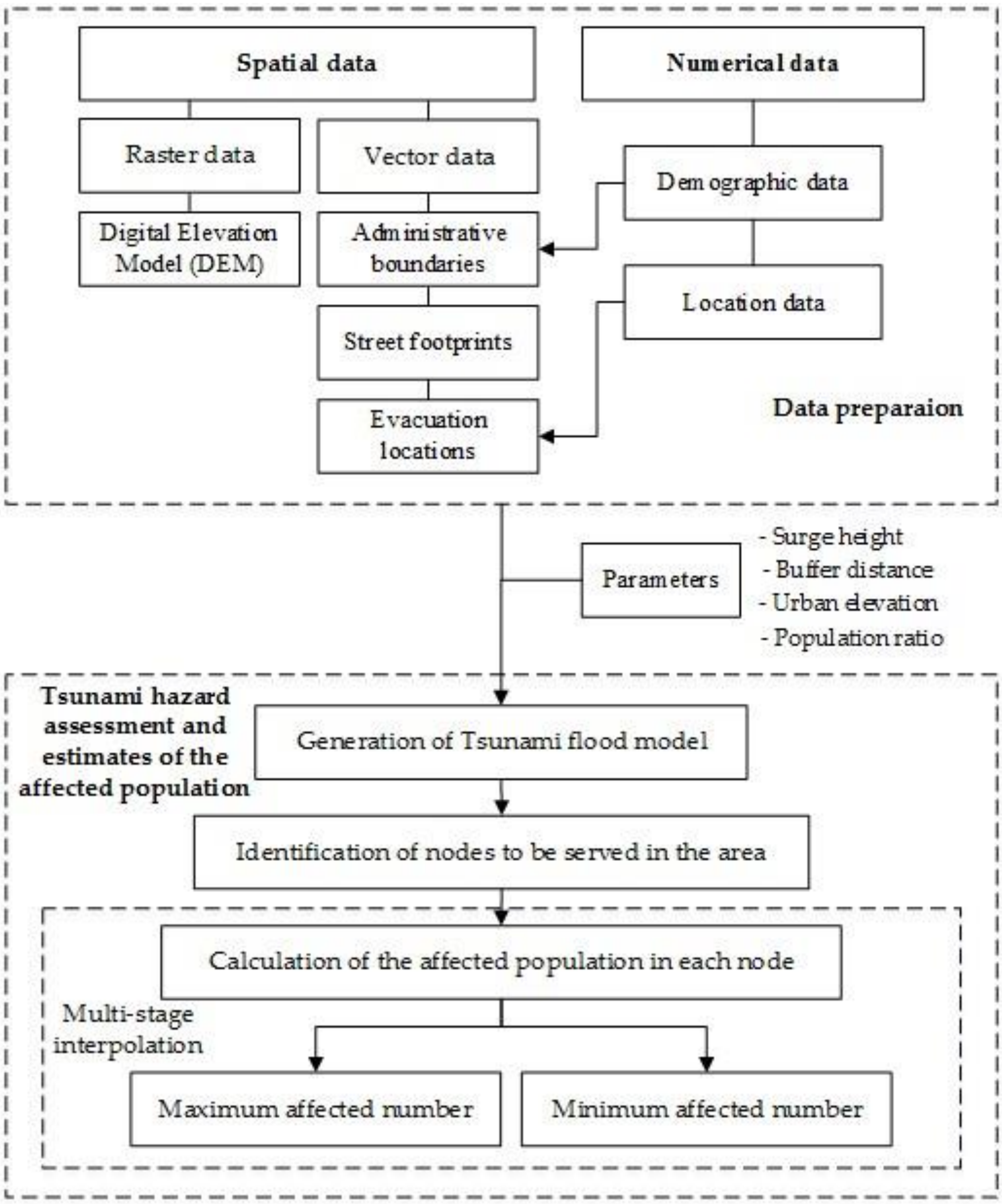


Figure 5-2: The overall process of estimating the affected population.

This section is twofold. First, the areal interpolation techniques used for population estimation are described and illustrated by a given example. The second part explains the analytical operations for estimating the population affected by tsunami flood inundation in the GIS environment.

5.4.1 Areal interpolation techniques

The simple area-based method was developed in the early age of interpolation studies. This approach is based only on the overlap of the vector polygons of the source and target zones. The method has the advantage that it can be simply implemented in ArcGIS, and no assisting data are required in its process. The function was formulated by Fisher and Langford (1995) and is described as follows:

$$P_t = \sum_{s=1}^{S} \frac{A_{ts} P_s}{A_s} = \sum_{s=1}^{S} A_{ts} d_s \tag{1}$$

where P_t is the estimated population of target zone *t*; A_{ts} is the area of overlap between target zone *t* and source zone *s*; P_s is the population of source zone *s*; A_s is the area of source zone *s*; *S* is the number of source zones; and d_s is the average population density of source zone *s*. This simple areal weighting, however, does not imply the actual population spatially distributed in a geographic area. Thus, the use of a rigid concept of the area-based technique may not be sufficient for obtaining good estimations. Renovating and combining its model to other interpolation methods would improve the estimation accuracy, particularly for a small area.

This research, therefore, proposes a multi-stage areal interpolation for population estimation using GIS. As the area-based method is criticised in the literature as an oversimplified assumption, an area-based method is applied from a different view in the initial stage. The dasymetric-mapping method using street footprint GIS data is therefore used in the next stages to estimate the disaster-affected population for a smaller area. By doing this, each interpolation stage requires digital maps in the GIS environment. Within ArcGIS, every dataset has a coordinate system and thus all vector GIS data must be in the same coordinate system and projection in order to perform integrated analytical operations such as overlaying vector layers.

The first stage of interpolation requires three GIS maps, which are source-zone boundaries, target-zone boundaries, and remote sensing images. The purpose of this stage is to estimate the population by subdividing the source zone into smaller spatial units, which is a target zone that has better consistency with the population distribution. In this regard, the population data in the source zone are combined with its remote sensing data to obtain a feasible area that infers the most-likely population distribution, which is the target zone. In other words, the population data at the source zone level are spatially reallocated to predict the population of the target zone based on its geographic characteristics. Thus, the weight in this step is not the proportion of the target and source zone areas as shown in equation (1). Instead, the ratio of the population figures in the target zone and the source zone acts as a weighting factor. This population-weighted ratio is estimated based on the remote sensing and population data held by decision makers. Also, the decision makers' subjective view could be combined with those datasets to estimate the ratio. As a result, a new equation of areal interpolation in the initial stage can be formulaically described as:

$$P_t = \sum_{s=1}^{S} P_s r_{ts} \tag{2}$$

where P_t is the estimated population of target zone *t;* P_s is the population of source zone *s;* *S* is the number of source zones; and r_{ts} is the ratio of population between target zone *t* and source zone *s*.

Figure 5-3 shows the study area as a source zone that covers an area of 19.18 km^2 with a total population of 20,628. The target zone occupies an area of 7.34 km^2. An example in Figure 5-3 (a) is the traditional area-based interpolation, which aggregates population data from the source zone to the target zone by computing a weight for the overlap zone between the source and target zones. The intersection zone occupies 38% of the source zone. Thus, the estimated population in the target zone can be calculated by substituting A_{ts} = 7.34 km^2, A_s=19.18 km^2, and P_s=20,628 in equation (1):

$$P_t = \sum_{s=1}^{1} \frac{A_{ts}P_s}{A_s} = \left(\frac{7.34}{19.18} \times 20{,}628\right) = 0.38 \times 20{,}628 = 7{,}894 \tag{3}$$

In contrast, Figure 5-3 (b) gives a different perspective of cartographic areal interpolation using the population-weighted technique coupled with remote sensing images to draw the area in which the dwelling units are mostly distributed. According to the remote sensing and population data, the ratio is suggested by a decision maker as 90% (r_{ts} = 0.9), for example. This means that another 10% of the population is scattered in an area outside the target zone, which perhaps is a non-residential area. Therefore, the population in the target zone can be estimated by substituting r_{ts}= 0.9, and P_s=20,628 in equation (2):

$$P_t = \sum_{s=1}^{1} P_s r_{ts} = (20{,}628 \times 0.9) = 18{,}565 \tag{4}$$

The estimation solutions provided by the two methods are significantly different. The estimation in the target area shows a population of 7,894 using the traditional area-weighted technique. On the other hand, the population-weighted method with the assisting data provides a population estimate of 18,565 in the target zone. Thus, it is essential to evaluate these results in terms of accuracy, as implementing accurate population estimates in disaster relief can contribute to efficient and effective humanitarian logistics.

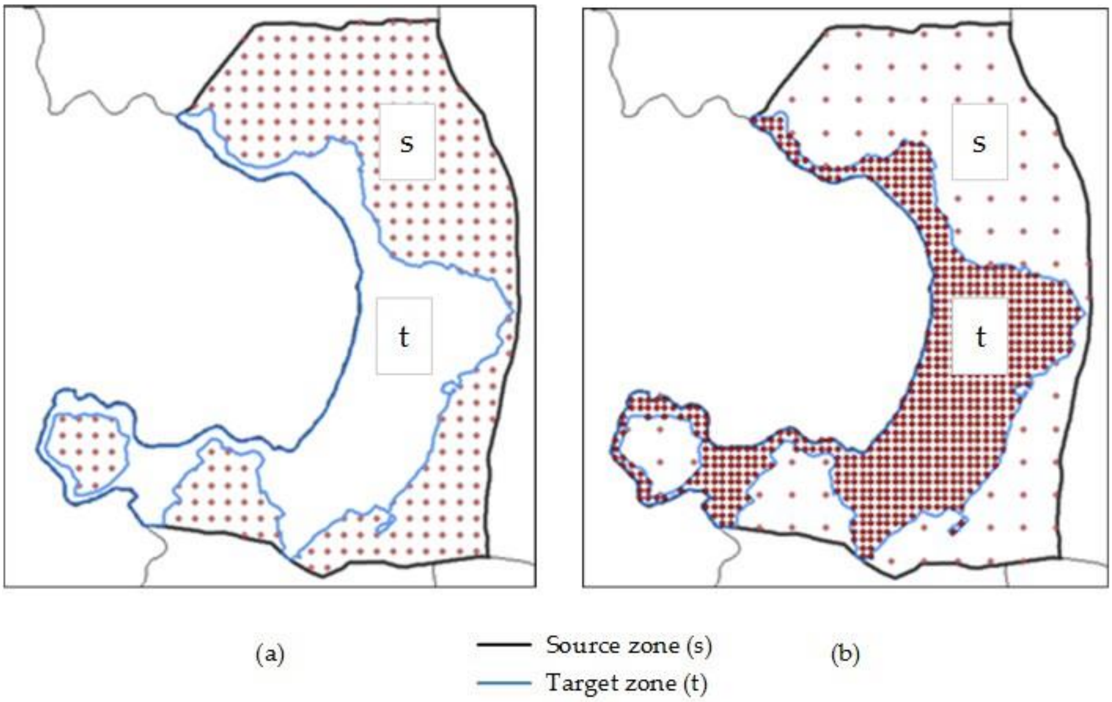


Figure 5-3: A comparison of the new perspective and traditional area-based interpolation.

In order to evaluate the population estimation provided by the above methods, collecting population counts in the area may consume too much time and cost. Thus, areal photographs can be used to superimpose the study area for a visual presentation in order to assess the estimated results without any excessive time or cost. Figure 5-4 illustrates the overlaying of the study area and its remote sensing image. As can be seen in the areal photograph, most residential units are located in the target area, whereas the outer area occupies a range of mountains with very few dwellings. This can imply that taking the geographic characteristics of an area into area-based interpolation to identify population weighting can provide a more realistic solution for population distribution.

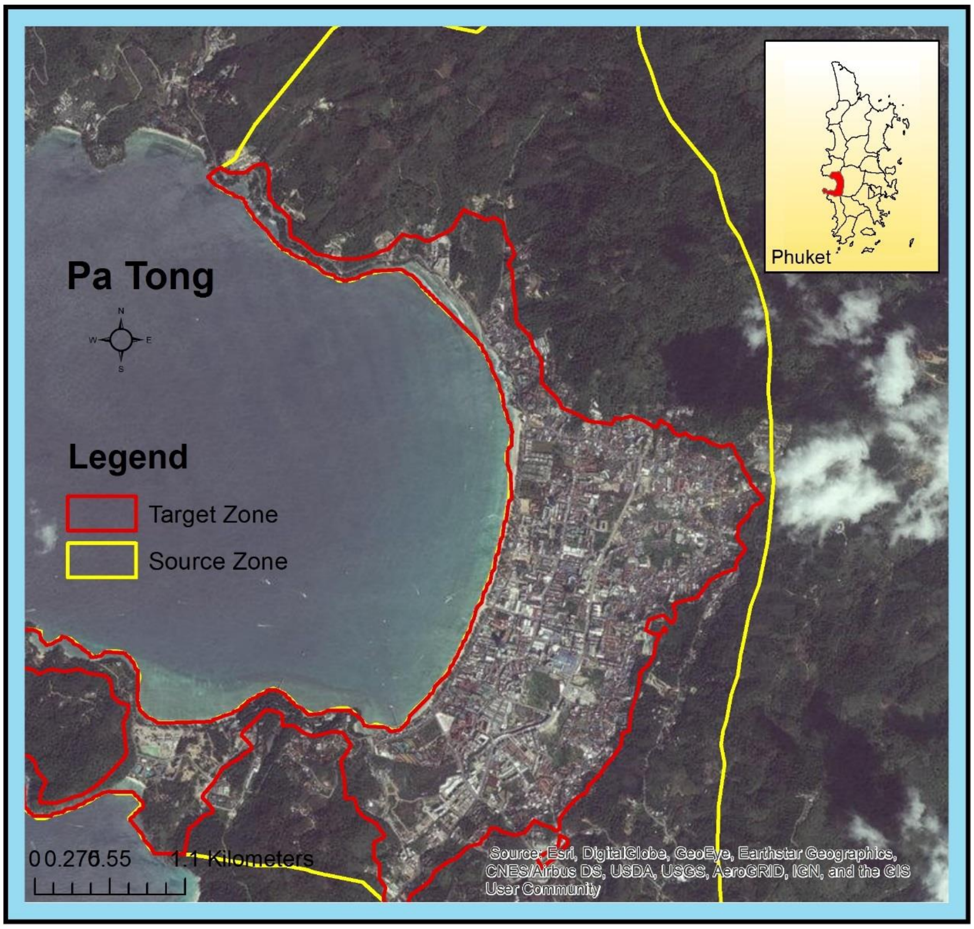


Figure 5-4: Population-estimation evaluation using remote sensing imagery.

The second stage of areal interpolation is to use the street-weighted technique. In this stage, three GIS vectors are needed for analytical operations: the source-zone boundaries, the target-zone boundaries, and the street vectors. When overlaying, the street weight for each intersection area is calculated as the ratio of the street length in the overlap zone to the street length in the source zone. The proportion estimate for a given target zone can be calculated according to the following function (Reibel and Bufalino, 2005):

$$W_{st} = \frac{\sum L_{st}}{\sum L_s} \tag{5}$$

where W_{st} is the weight for a given intersection-area fraction defined by its unique pair of source and target zones; L_{st} is the length of the street vector in that intersection zone; and L_s is the length of the street vector in the source zone.

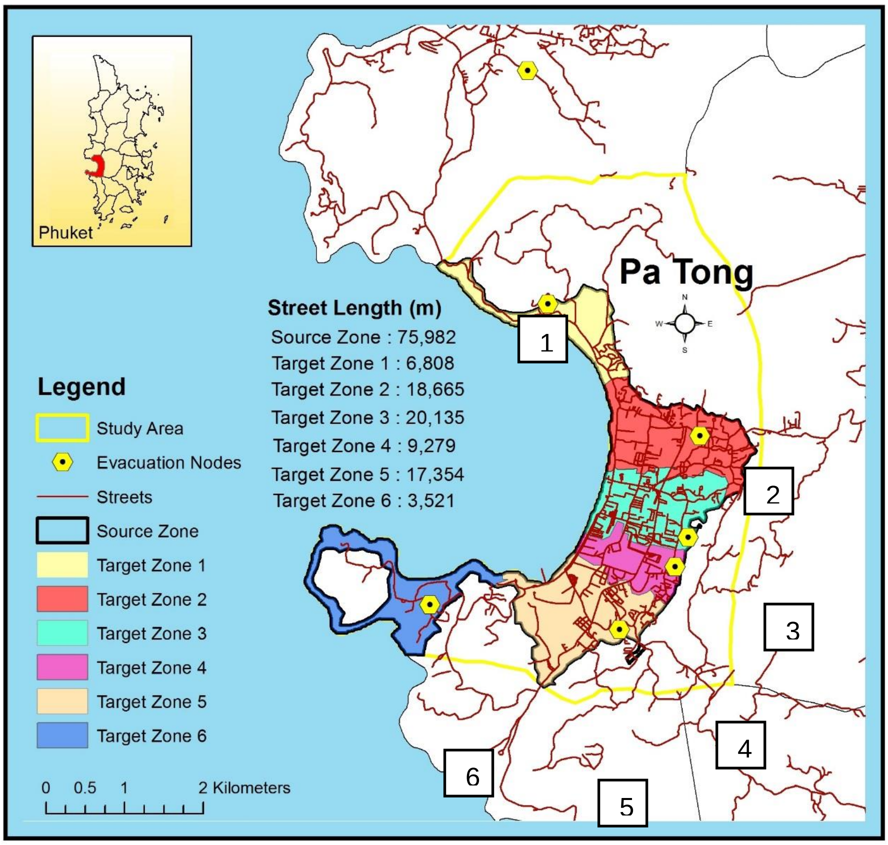


Figure 5-5: The GIS vector data for the street-weighted approach.

In order to obtain the population estimation in the target zone, the weight for the intersection zone is multiplied by the population counts in the source zone. This results in an estimate of the target-zone population aggregated from the source zone based on street weighting. The concept of street-weighted interpolation is also applied in the next steps to improve the estimate by subdividing the zone into a smaller area.

In this case study, the target zone defined in the first stage will become the source zone when moving into the second stage. The new source zone is then divided into a number of smaller areas depending on a number of evacuation nodes. The neighbourhood of each node, in turn, transforms into a target zone. Figure 5-5 shows the GIS vector data including the source zone and its subdivided target zones in accordance with the evacuation locations.

To illustrate the street-weighted interpolation technique in the second stage, the length of each street vector in the source zone and in each target zone first has to be summed. The summation of the street length in each zone is simply obtained from the attribute data table of the street vector in ArcGIS. Subsequently, each intersection-zone fragment is defined by its source zone and identical target zone pair. For example (see Figure 5-6), the intersection-zone fraction of the length of the street vector in the node 3 neighbourhood and the length of the street vector in the source zone can be calculated by substituting L_s=75,982, and L_{st}=20,135 in equation (5):

$$W_{st} = \frac{20,135}{75,982} = 0.265 \tag{6}$$

Thus, the estimate of the population in this node neighbourhood is the outcome of multiplying W_{st} in equation (6) by P_t in equation (4):

$$P_{node\,3} = 0.265 \times 18,565 = 4,919 \tag{7}$$

The population in an evacuation-node neighbourhood has been estimated using the street-weighted interpolation technique in the second stage. In the next stage, the flooded areas that are generated from the tsunami vulnerability model with a parameter of a 10-metre tsunami surge are used for superimposition over each evacuation-node neighbourhood to find the intersection-zone between the flooded area and its evacuation neighbourhood. As a result, an area flooded by a tsunami surge in each evacuation zone is drawn within ArcGIS. The flooded area becomes a target zone for its identical evacuation area which has inversely changed to the source zone in the next stage of the street-weighted interpolation.

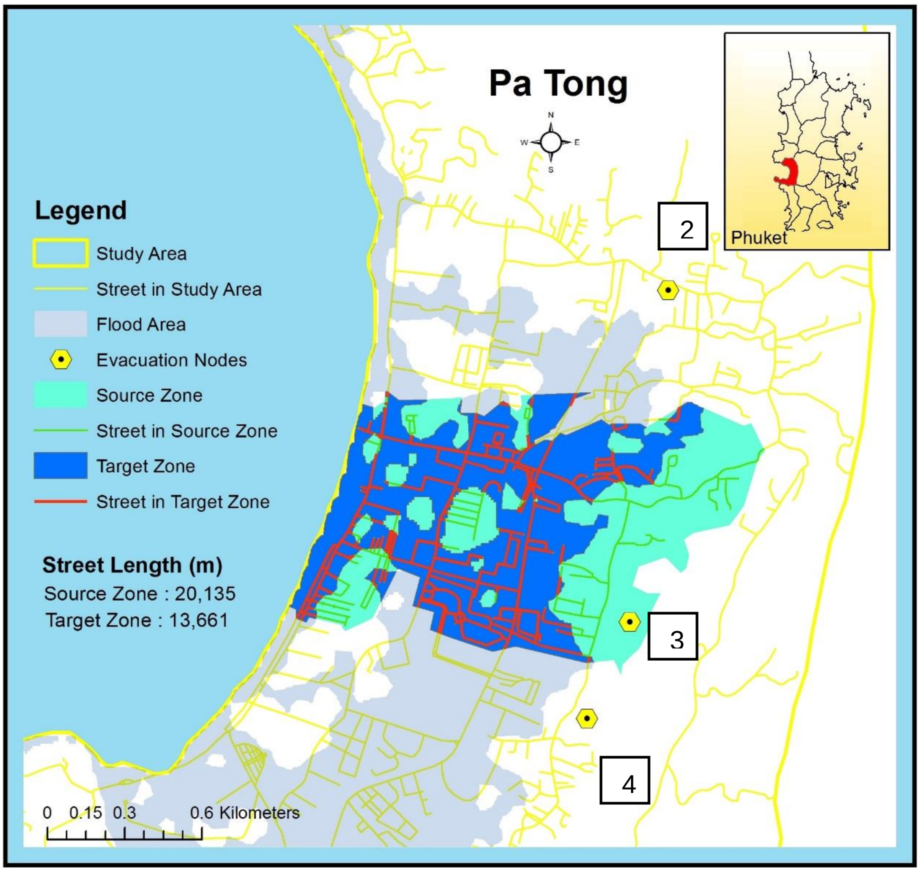


Figure 5-6: An example of estimating the population affected by tsunami flooding in an evacuation-node neighbourhood using the street-weighted interpolation technique.

The last stage is utilised to estimate the population affected by the tsunami flood. This final step also uses the street-weighted interpolation method for the population estimation. The processes of interpolating are again operated as in the second stage using equation (5). The ratio of the total length of the street vector in the intersection zone to the total length of the street vector in the source zone is also calculated as a weight factor. The different context is that the source zone is an evacuation-node neighbourhood, while the target zone is an inundated area. Figure 5-6 shows the overall view of the tsunami flood in the study area and demonstrates the node 3 neighbourhood for guidance in estimating the population that lives in the flooded area. By substituting L_s=20,135 and L_{st}=13,661 in equation (5), the number of people directly affected by the tsunami flooding in the area of evacuation node 3 is estimated in the following steps:

$$W_{st} = \frac{13,661}{20,135} = 0.68 \tag{8}$$

Hence, the estimate of the population living in the flooded area of location 3 is the result of multiplying W_{st} in equation (8) by P_t in equation (7):

$$P_t = 0.68 \times 4,919 = 3,344 \tag{9}$$

The estimate of the population in the target area, P_t in equation (9) infers the number of people who are dwelling in a node 3 neighbourhood and directly affected by the 10-metre tsunami wave for this example. In this chapter, P_t in equation (9) is defined as the minimum population affected as these numbers receive the direct impact from the flood. P_t in equation (7) refers to the maximum number exposed to the tsunami. In this regard, it is an assumption that people living outside the path of a disaster may experience secondary effects from the incident. The maximum affected, therefore, are the total number of people who live in an evacuation-node neighbourhood, including those directly and indirectly affected. The final solution for the node 3 example then can be concluded, that is, the estimate of the population affected by the tsunami flood falls into the range of a minimum of 3,344 and a maximum of 4,919 people. This policy therefore may assist a decision maker to avoid either overestimating or underestimating the affected population. Bear in mind that this solution gives merely a preliminary estimation of the affected population in the disaster area. Identifying the exact number in the range is nearly impossible in a real situation. However, the decision maker may utilise simulation or mathematical techniques to predict the most likely possible outcome in the range. This depends on a number of decision-making factors, such as the unique characteristics of the area and the historical data of the disaster.

5.4.2 GIS analytical operations

This section describes the integration of a methodology that estimates the population exposed to a tsunami inundation within the GIS environment. The functionalities of ArcGIS 10.3 are used to build a tsunami vulnerability model of the study area. The GIS features the datasets of a model that are used to perform various spatial analyses using the geoprocessing tools with the aim of estimating the population affected by a scenario of tsunami flooding. The GIS analytical operations for the estimation can be divided into five phases as shown in Figure 5-7. The steps of GIS operations in ArcMap are demonstrated in Appendix E.

In the first phase of the operations, the spatial analysis of the study area requires population data, digital elevation terrain models, feature data of the administrative boundaries, street footprints, and evacuation location data. All the datasets are acquired from the different sources described in section 2. In the second phase, a set of parameters is required from the users to model a flooding vulnerability area. Moreover, the level of uncertainty in estimating the population affected in the vulnerability model depends on decision-making variables, which include (1) the tsunami surge height, (2) the buffer distance from the flooding path, (3) the urban boundary where people are grouped densely, (4) the population ratio of (3), and the total population of the study area. Therefore, the proposed method involves the characteristics of the study area and its modelling of the flood vulnerability region during the preliminary phases of the operations.

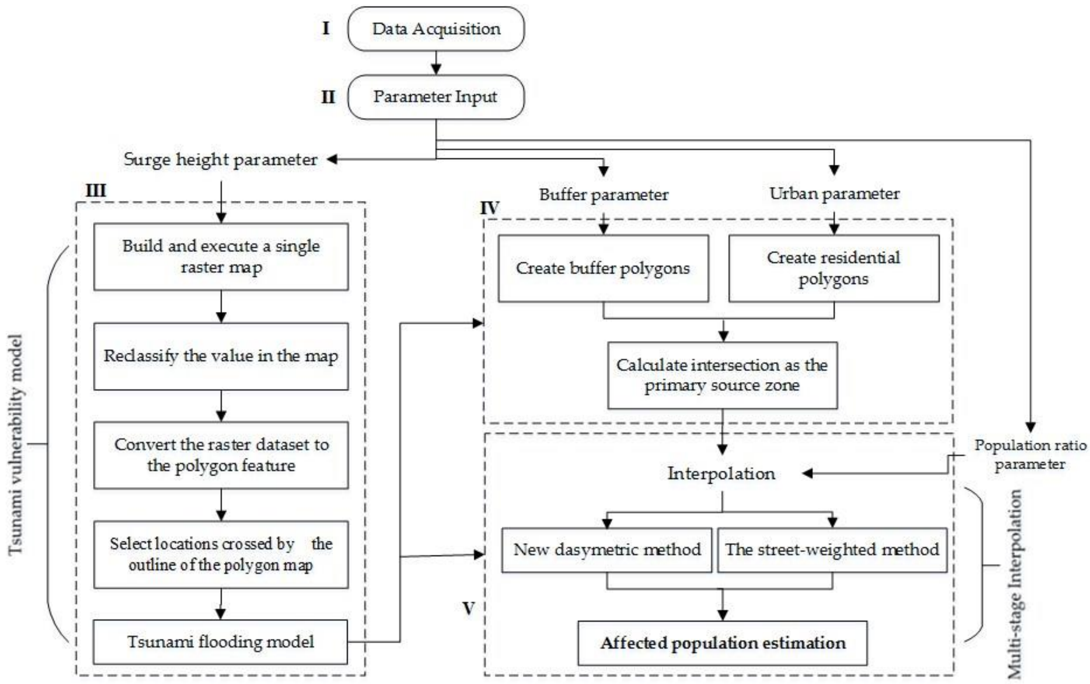


Figure 5-7: Phases of the GIS analytical operations.

In phase 3, the aim is to model the coastal tsunami flooding using a raster elevation dataset with the polygon boundaries of the study area. The geoprocessing tools in ArcGIS 10.3 can identify what parts of the raster or the extent to which the study area would be flooded under a variety of scenarios depending on the input parameters. A tsunami vulnerability model of the study area is generated as a result of GIS processing in this phase. The characteristics of the model and its feature datasets are repeatedly used in the rest of the operations.

Once the flood inundation model has been built, another two input parameters, buffer distance and urban elevation, are used for the spatial analysis in phase 4. The urban elevation parameter here refers to a specific value of terrain elevation where people are densely distributed and most likely to be affected. The most detailed population data available are limited to the geographic boundary of the study area. This is too coarse to use for the whole area of the town to estimate the affected population. Thus, it would be meaningful to downscale the study area to predict for smaller areas where real communities are mostly settled. This may result in a more detailed view of the distribution of the population within the town. With regard to the buffer distance parameter, a distance buffer from the flood line may give the decision maker the buffer area for predicting the indirectly-affected population. As mentioned above, people living outside the primary affected area may also experience some negative impacts as a result of the disaster strike. Therefore, defining an area as being indirectly affected can result in an estimate of the secondary affected population. This is true because when a disaster occurs, the total number affected usually includes not only those who are in the path of the disaster, but also a number of people living outside the devastated area.

After an additional two polygons are generated in the study area by the given parameters, the two vector polygons are then computed to find the intersection zone. This overlapped area is then used as the source zone for initiating the population estimation in the final phase, in which areal interpolation techniques are employed. This final phase requires the population ratio parameter, which is the population in the source zone that is used as an initial step of the multi-stage interpolation techniques described above. Finally, the last operation produces the numerical results of the affected population. To test the approach, the GIS-based application for the affected population estimation is demonstrated in the next section with a number of tsunami flood scenarios.

5.5 Experimental Results

This proposed approach offers various advantages by using areal interpolation techniques to estimate the affected population by using GIS. Not only are numerical terms produced as a result of executing the application, but also graphical solutions are provided as an alternative media in the GIS environment. Decision makers are able to use both types of solutions simultaneously in order to increase the efficiency of delivering aid to evacuation locations. This section illustrates the proposed GIS-based application and tests the solutions with different flood scenarios using an Inter ® Core ™ i5-3360M CPU computer with a memory of 6.00 GB on a Windows 7 operating system.

5.5.1 A GIS-based application for estimating the affected

The application starts with the extraction of the GIS data from the geographic database (GDB) to construct a tsunami vulnerability model. Figure 5-8 shows the GUI of the application in which a digital elevation model of the study area and a set of parameters are entered. A flooding scenario is generated in the form of a geographic map with its attribute data in the ArcGIS system, depending on the input parameters. The attribute data table contains all kinds of data on the flooding map. A set of data in the table is used for querying, analysing, and integrating with other parameters to estimate the population in the affected area. A Python scripting language is implemented to execute geo-processing tools in order to perform spatial analysis and data management in the ArcGIS platform. As a result, the application directly yields the numerical solution for the decision maker on the screen. The solution is also connected to ArcGIS for alternative visualising maps, which illustrates the extent of the tsunami inundation in the study area.

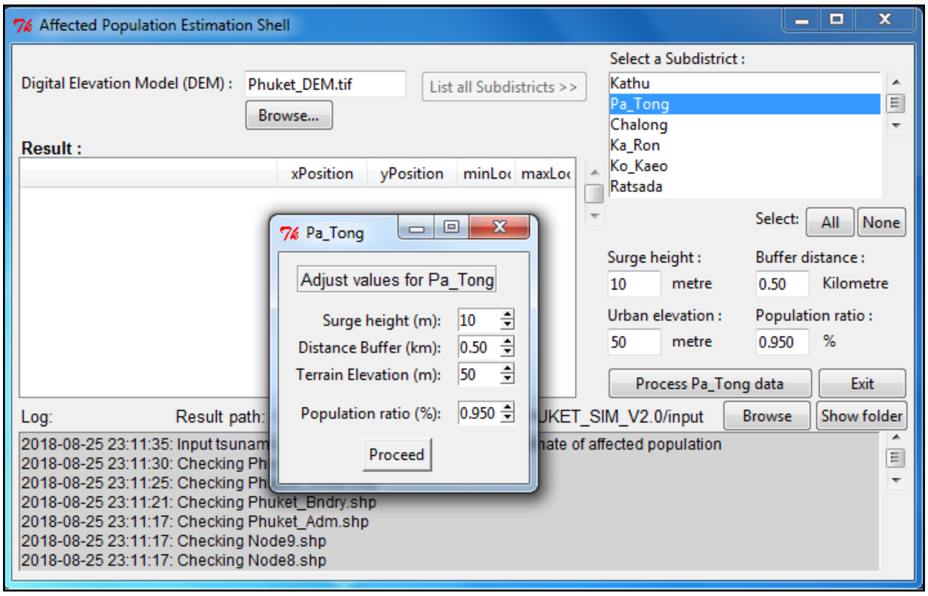


Figure 5-8: GUI and data and parameters input of the application.

5.5.2 Experimental results

To discuss the application solutions, several flood scenarios using different sets of input parameters are conducted so that the solutions can be compared and then analysed. Prior to comparing the results, the worst-case scenario, with the 10-metre surge reported in 2004, is used as the threshold problem and is solved first with the following input parameters: tsunami surge height (s) = 10, buffer distance (b) = 0.5, urban elevation (u) = 50, and population ratio (p) = 95%. The numerical solutions of the threshold scenario are shown in Table 5-1.

As the solutions are linked to ArcGIS, the identical results in terms of visualisation are provided with their attribute data so that they can be analysed further by the decision maker.

Scenario	**Parameter**				**Numerical solution**		
	Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)	Evac. node	Min. affected (person)	Max. affected (person)
Threshold	s = 10	b = 0.5	u = 50	p = 95	1	572	1,747
					2	1,005	4,705
					3	3,521	5,193
					4	1,463	2,393
					5	2,540	4,476
					6	236	908

Table 5-1: Numerical results for the threshold scenario.

The following scenarios are then proposed by merely altering one parameter, while the rest of the parameters continue to have the same values. This experiment is divided into three groups of scenarios, each of which trials three different values for the identical parameter: (1) surge height, (2) buffer distance, and (3) urban elevation and the population ratio. It is a fact that urban elevation is critically related to the population ratio, as the level of urban elevation always affects a fraction of the population, and therefore, both parameters are characterised in the same group. Table 5-2 shows each scenario group that corresponds to its parameter test, while the solutions for each scenario group are illustrated in Tables 5-3, 5-4 and 5-5.

Group	**Scenario**	**Parameter test**
1	1	Surge height
	2	
	3	
2	4	Buffer distance
	5	
	6	
3	7	Urban elevation & Population ratio
	8	
	9	

Table 5-2: Parameter test in each flooding-scenario group.

The first scenario group outputs the estimates of the population affected by a set of different surge-height parameters. Scenarios 1, 2, and 3 examine the results when using the parameters of s = 9, s = 8, and s = 7, respectively, while other parameter values remain the same as specified in the threshold scenario. A range of minimum and maximum populations is produced as the estimation for each evacuation location in the study area. The notable observation when changing the surge-height value is that the minimum number affected is directly proportional to the tsunami surge height. Specifically, when the surge height is reduced to 9, 8, and 7 metres, the number of people directly affected by the surge in evacuation node 3, for example, decreases to 2,854, 1,501, and 864 people, respectively (see Table 5-3).

Scenario	Parameter				Numerical solution		
	Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)	Evac. node	Min. affected (person)	Max. affected (person)
1	$s = 9$	$b = 0.5$	$u = 50$	$p = 95$	1	396	1,743
					2	758	4,511
					3	2,854	5,193
					4	1,263	2,393
					5	2,437	4,476
					6	224	908
2	$s = 8$	$b = 0.5$	$u = 50$	$p = 95$	1	113	1,740
					2	436	2,044
					3	1,501	5,011
					4	1,086	2,393
					5	2,244	4,476
					6	156	908
3	$s = 7$	$b = 0.5$	$u = 50$	$p = 95$	1	153	1,738
					2	302	1,680
					3	864	4,329
					4	988	2,393
					5	1,991	4,476
					6	103	908

Table 5-3: Numerical results of scenarios 1-3.

With respect to the maximum affected, the numbers very slightly fluctuate in most evacuation locations compared to the threshold scenario. However, the maximum numbers in some areas could be significantly decreased, especially when the tsunami surge is lower. This depends on the characteristics of an area. For instance, node 2 in scenario 1 (s = 9) shows a minor decrease in the maximum affected population of 4511 people compared to the threshold (s = 10) of 4705 people. Nevertheless, there is a significant reduction in the maximum numbers for node 2 when the surge height drops to 8 or 7 metres; the numbers are 2044 and 1680 people, respectively.

Scenario	Parameter				Numerical solution		
	Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)	Evac. node	Min. affected (person)	Max. affected (person)
1	$s = 10$	$b = 0.3$	$u = 50$	$p = 95$	1	572	1,657
					2	1,005	3,790
					3	3,521	5,193
					4	1,463	2,393
					5	2,640	4,476
					6	236	856
2	$s = 10$	$b = 0.2$	$u = 50$	$p = 95$	1	572	1,508
					2	1,005	3,078
					3	3,522	5,082
					4	1,464	2,358
					5	2,649	4,431
					6	236	607
3	$s = 10$	$b = 0.1$	$u = 50$	$p = 95$	1	572	887
					2	1,005	2,264
					3	3,521	4,807
					4	1,464	2,118
					5	2,640	4,017
					6	236	435

Table 5-4: Numerical results for scenarios 4-6.

Scenarios 4, 5, and 6 assess the solutions with respect to buffer distance. This parameter of distance away from the flooding line is assessed using the values of $b = 0.3$, $b = 0.2$, and $b = 0.1$ correspondingly. The other parameters are identical as in the threshold problem. As a result, when comparing solutions, a decreased buffer distance leads to the reduction in the maximum affected number in every evacuation node. In contrast, the minimum affected remains the same number between two matching nodes. Thus, altering the buffer distance amount will affect the maximum numbers only (see Table 5-4). This implies that the value of the distance away from the flood line is directly proportional to the total estimate of the affected population.

Scenario	Parameter				Numerical solution		
	Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)	Evac. node	Min. affected (person)	Max. affected (person)
1	$s = 10$	$b = 0.5$	$u = 40$	$p = 80$	1	353	1,270
					2	892	4,056
					3	3,127	4,611
					4	1,300	2,094
					5	2,344	3,761
					6	178	654
2	$s = 10$	$b = 0.5$	$u = 30$	$p = 70$	1	314	827
					2	845	3,599
					3	2,961	4,322
					4	1,231	1,938
					5	2,220	3,311
					6	135	426
3	$s = 10$	$b = 0.5$	$u = 20$	$p = 60$	1	271	557
					2	793	2,978
					3	2,778	3949
					4	1,155	1,750
					5	2,082	2,867
					6	108	272

Table 5-5: Numerical results of scenarios 7-9.

In the aspects of the urban elevation and the population ratio, these two factors are regarded as the area in which people are densely distributed and most likely to be affected by tsunami inundation. Thus, when the amount of urban elevation is adjusted, the population figures have to be changed consistently with the amended area. For example, an urban elevation of 50 metres above sea level is considered to be an area where 95 per cent of the total population is settled, and this populated region is vulnerable to tsunami flooding. Thus, the population ratio is interpreted as 95 per cent. In this experiment, flood scenarios 7, 8, and 9 then consider urban elevation followed by its population fragment to examine the affected population estimation, giving parameters of $u = 40$ with $p = 80$, $u = 30$ with $p = 70$, and $u = 20$ with $p =$

60, respectively. There is no change in the other parameters in order to properly control the inspection. The results show that these two parameters affect both the minimum and maximum numbers when compared to the threshold scenario (see Table 5-5). The reduction in the urban elevation value will downscale the study area resulting in a decreased population. By doing this, each neighborhood in the evacuation node may cover a smaller area with a smaller number of residents. As a result, there is a reduction in the estimation of both the minimum and maximum affected.

Bear in mind that there is a control of the variables in each flood scenario in order to examine the extent to which parameters affect the solution. Accordingly, more scenarios can be conducted when each input variable is adjusted. In a real situation, most parameters can be periodically obtained in the phase of disaster preparedness. However, the tsunami surge height is revealed by the Deep Ocean Assessment and Reporting of Tsunami System (DART) only once an earthquake stimulates a series of tsunami waves. This allows the relief supply centre in the study area to estimate the affected population using this GIS-based application. The estimates can be used as a vital decision-making factor in planning and managing relief deliveries for the affected population in a timely manner.

5.6 Chapter Summary

An inefficient logistics response to the 2004 Asian tsunami in Thailand was in part result of a failure to estimate the spatially-distributed population affected by the tsunami inundation. This chapter therefore proposes a powerful tool to integrate the techniques for estimating the affected population and the ability of GIS in the disaster context. The aim is to estimate the affected numbers based on tsunami vulnerability areas associated with a set of parameters. The innovative aspect of the proposed approach is the estimation of a range of the minimum and maximum population affected by the tsunami inundation for a small area. This GIS-based application can be used not only in the disaster preparedness phase to study tsunami flood scenarios, but also in the response phase after the tsunami onset to efficiently manage delivery routing for humanitarian relief, which critically depends on the affected numbers. The use of the application simply begins by entering the data and decision-making parameters. A tsunami vulnerability model is then generated in the GIS environment. This model provides a geographical format with its attribute data in ArcGIS that is used as the primary information for the multi-stage interpolation processes. Regarding the population estimation technique, the population-weighted interpolation with assisting information is proposed in this chapter in the first stage. The weighted-street methods are used in the subsequent stages for the estimation and analysis of small areas. The latter could be enormously advantageous in cases when the availability of population data in subareas is limited.

The proposed approach was piloted in Patong, Phuket to demonstrate its operability for assessing affected areas when a tsunami occurs. The integration of GIS and interpolation techniques by means of the proposed application can efficiently produce estimates of the affected population in each evacuation location. In the experiments, the average of the CPU time is 257 seconds to obtain the solutions for a flood scenario. The estimates provide useful information not only in the form of direct numerical results but as a visualisation map in the ArcGIS system. The outcome of the GIS-based application is expected to be used as a vital source of information that provides decision makers with the ability to plan and manage vehicle routing for humanitarian relief in the aftermath of a tsunami.

Chapter 6: The CVRP with Simulated Demand

6.1 Introduction

Quick response to the urgent need for relief in affected areas right after disasters is a critical issue for emergency logistics, which has recently aroused growing concerns and research interests due to the occurrence of several large scale natural disasters. As a result of the Indian Ocean tsunami in 2004, for example, application of logistics to disaster relief operations has received a great deal of attention from both researchers and practitioners (Kovács and Spens, 2007). In fact, the tsunami provided evidence that the effectiveness of the humanitarian aid response critically depends on logistic speed and efficiency (Pettit and Beresford, 2005), resulting in increasing the awareness of the crucial role of logistics in humanitarian relief operations (Tatham and Christopher, 2014).

With these concerns, the subject of the vehicle routing problem (VRP) has become a focus of interest even though a great deal of VRP research has put greater emphasis on commercial logistics. On the humanitarian side, the routing of vehicles carrying critical supplies can greatly impact the relief operations in the aftermath of a disaster. Distributing vehicles with restricted loads of supplies in an efficient manner is the most important issue for the survival of affected people. Thus, applying the capacitated VRP (CVRP) can be useful in the allocation of aid items to the disaster field.

The CVRP is one of the most widely studied topics in the field of logistics and transportation. However, the CVRP studies have not attracted much attention among researchers in the field of humanitarian logistics, and most of them are valuable in gaining an initial understanding of this field (Beamon and Kotleba, 2006; Kovács and Spens, 2007).

Therefore, it is worth considering the CVRP and potential solution approaches in the emergency environment for the purpose of alleviating people's suffering from a disaster. To this end, this chapter presents the CVRP with simulated demand for humanitarian logistics by using the Phuket tsunami-prone area as a case study. The main feature of this logistics dilemma is the adoption of a demand simulation, as measuring actual demand in a disaster situation is nearly impossible due to the emergency nature. Thus, demand data here are proportionally derived from the affected numbers estimated by the GIS-based method proposed in the previous chapter. However, an additional aspect of dynamic population, vacationers, is considered in this chapter because Phuket is a popular tourist spot. As a result, the total demand for each evacuation node is principally the sum of residents' and vacationers' demands, which are randomly derived from uniform distribution and normal distribution respectively. For simulation technique, the Monte Carlo Simulation (MCS) is applied to allocate an amount of demand, which is randomized based on a set of decision parameters, to each evacuation node. All demands made by the MCS then become an essential ingredient of the proposed solution method, the Clarke and Wright Savings (CWS) heuristic, for solving the CVRP. Moreover, another important highlight of the solution is that not only is the cost minimized, but route priority and resource efficiency are also generated as ancillary information for decision makers to plan and manage humanitarian logistics in the planning stage, as well as in real-time decision making in the response stage.

6.2 Literature Review

The capacitated vehicle routing problem (CVRP) is a combinatorial optimization and integer-programming problem that seeks to find the most efficient utilization and routing of a vehicle fleet to service a set of customers subject to constraints. The CVRP was first introduced by Dantzig and Ramser (1959), who considered the routing of a truck fleet delivering gasoline from a central terminal to a set of service stations.

The CVRP is one of the most widely studied topics in the field of operations research (OR) and has received the great attention in the scientific literature. The CVRP is extensively studied because of its wide applicability and its importance in determining efficient strategies for reducing operational costs in distribution networks (Kumar and Panneerselvam, 2012). In the traditional CVRP, all the customers correspond to deliveries, and the deterministic demands cannot be split. A homogenous fleet of vehicles is based at a single central depot, and only the capacity constraints for the vehicles are imposed.

In the literature, there has been significant research focusing on either the CVRP (e.g. Baldacci *et al*., 2010; Laporte and Nobert, 1987; Toth and Vigo, 2014) or its different variants including VRP with time windows (VRPTW) (e.g. Kenyon and Morton, 2003; Kallehauge, 2008; Moccia *et al*., 2012), pickup and deliveries and periodic VRP (e.g. Solomon and Desrosiers, 1988), dynamic VRP (DVRP) (e.g. Psaraftis, 1995), periodic VRP (PVRP) (e.g. Mourgaya and Vanderbeck, 2006), Split Delivery VRP (SDVRP) (e.g. Archetti and Speranza, 2008) and open VRP (OVRP) (e.g. Sariklis and Powell, 2000; Pichpibul and Kawtummachai, 2013). However, several studies consider only deterministic VRP, which normally contains static elements in the problem. The VRP model sometimes fails to capture some important aspects of real-life transportation and distribution-logistic problems. This is due to the fact that several of the problem parameters, such as demand, are uncertain by their nature and, as a result, are often oversimplified and treated as deterministic (Ak and Erera, 2007).

There is a growing literature that addresses VRP in the humanitarian logistics domain. Knott (1987), in one of the earliest studies that considers distribution of food items from a central depot to several camps, formulates a linear programming model that determines the number of trips to each camp. The objective is to meet demand while minimizing transportation costs.

The later literature reports more complicated routing and scheduling problems and captures the inherent complexities of the humanitarian relief environment, including multiple commodities, multiple transportation modes or vehicle types, multiple periods, uncertain or varying demand and supply levels and transportation network conditions, and delivery time windows. The following have applied the VRP in the humanitarian field recently.

Barbarosoğlu and Arda (2004) study a two-stage programming model applicable for planning the distribution of relief items under demand and supply uncertainty. Their study is an extension of Haghani and Oh's (1996) work that addresses the deterministic problem of multiple transportation modes with multiple commodities in a disaster relief operation. The authors test their model with real data from the Turkey earthquake in 1999.

Özdamar *et al.* (2004) propose an emergency logistics problem with multiple suppliers providing multiple commodities to multiple depots. They formulate a mathematical model to determine the delivery routes and the quantities of goods to be carried for each route with the aim of minimizing the unsatisfied demand. The formulation is proposed for regenerating plans based on changing demand, supply and fleet size. An algorithm based on a Lagrangian relaxation heuristic is proposed to solve the problem and tested with data from the Turkey earthquake in 1999.

Sheu (2007) uses a hybrid fuzzy clustering-optimization approach based on a sequence of steps that rely on demand forecasting and aggregation techniques for affected areas. The proposed method involves two mechanisms: disaster-affected area clustering and relief co-distribution. The model is applied to data from an earthquake that occurred in Taiwan.

Balcik *et al.* (2008) consider a last-mile distribution problem in a network containing a central warehouse with a heterogeneous fleet. The objective is to determine delivery routes and facilitate decisions regarding inventory allocation by considering supply, vehicle capacity, and delivery deadlines. The authors propose a two-phase modeling approach with input and output stages. In the input stage, the candidate delivery routes for each vehicle are generated. Decisions about supplies are determined in the second stage. The objective is to minimize the sum of transportation costs and penalty costs due to unsatisfied and late-satisfied demand.

These studies, which focussing on the VRP in humanitarian logistics, consider a number of different objectives, including minimizing logistics costs, minimizing the amount of unsatisfied demand, and some other economic factors. However, the emergency VRP is different from general VRP, particularly in demand-related information and supply of emergency resources (Qin *et al.*, 2017). Furthermore, several existing studies focus on developing new algorithms for improving solutions, while the solution quality does not capture the whole perspective in the real-life emergency logistics (Laporte, 2007). Other qualities such as simplicity of implementation and flexibility area also important (Juan *et al.*, 2010).

According to the literature, the nature of VRP for humanitarian logistics is relatively complicated and hence difficult to solve, and therefore some potential challenges have been exposed in many studies. For example, demand in disaster response is urgent, while transportation resources are limited (Balcik *et al*., 2008; Ichoua, 2010). Besides, an emergency situation has high levels of uncertainty in terms of demand, supplies and assessment (Van Wassenhove, 2006). In addition, some pre-route operational tasks are essentially required, such as relief demand estimation, as well as efficient relief resource allocation to affected areas (Sheu, 2007). Thus, the most frequent issue of disaster response reported in the literature undoubtedly is the demand uncertainty.

This VRP research differs from the earlier studies in a number of aspects, including the consideration of simulation of demand that are derived from the estimates of population in the affected area. When acquiring simulated demand, resource efficiency can be examined in the preparation phase to determine whether the planned transportation resources like vehicle number and vehicle speed are sufficient within a deadline operation time. While in the response phase, a route priority is also provided to facilitate decisions to be made in case of insufficient supply resources.

6.3 The CVRP Formulation

The CVRP is defined as follows: Let G = (V, A) be a direct graph where V = {0, 1, 2, … , n} is the vertex set and A = $\{(i, j) : i, j \in V, i \neq j\}$ is the arc set. Vertex 0 represents the depot whereas the remaining vertices correspond to demand nodes, V* = V – {0}. Each arc represents a route from node i to j, and each node has a non-negative demand, q_i, to be delivered. The weight of each arc $c_{ij} > 0$

corresponds to the cost of moving from node i to j, and if $c_{ij} = c_{ji}$, then we are facing the symmetric VRP; otherwise, the problem is asymmetric. In this research, these c_{ij} are assumed to be symmetric ($c_{ij} = c_{ji}$, $0 \leq i, j \leq$ n). An unlimited homogeneous fleet, each with capacity Q, is assumed and available at the depot. Then, for a given cost matrix (c_{ij}), the CVRP is the following problem: determine a set of minimum cost routes and associated delivery quantities so that (i) each route starts at the depot, visits a subset of the evacuation nodes, and ends at the depot again; (ii) the delivery quantities of each route do not exceed the vehicle capacity Q; and (iii) the delivery amounts of all routes serving a node i add up to the demand q_i.

The CVRP model in this section is formulated using three-index binary variables $x_{i,j}^{k}$, as proposed by Golden et al. (1977), but is applied here to the relief logistics context instead of the commercial. The variables indicate whether vehicle k travels directly from node i to j ($x_{i,j}^{k}$ = 1 if vehicle k travels directly from node i to j, 0 if not).

Here, the CVRP formulation is given for the relief logistics environment. The list of variables must be identified as follows:

- G = (V, A)
- $V = \{0, 1, 2, \ldots, n\}$ where 0 represents the depot and $1, \ldots, n$ correspond to all the evacuation nodes, and $V^* = V - \{0\}$
- q_i = the demand of the evacuation node i, ($i \in V^*$)
- c_{ij} = the distance (cost) between nodes i and j, ($i, j \in V$)
- $K = \{k_1, k_2, \ldots, k_m\}$ represents number of vehicles

- Q = the capacity of each vehicle $k \in K$ (the fleet is identical)

The objective of the model is to minimize the total distance with respect to the essential constraints. The mathematical model of the CVRP is presented below based on the formulation given by Bodin *et al*. (1983). The model is described as follows:

$$min \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}^{k} \quad (1)$$

Subject to:

$$x_{ij}^{k} = \begin{cases} 1 & \text{if the vehicle } k \text{ travels from node } i \text{ to } j \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$\sum_{k \in K} \sum_{i \in V} x_{ij}^{k} \geq 1, \quad \forall j \in V * \quad (3)$$

$$\sum_{k \in K} \sum_{j \in V} x_{ij}^{k} \geq 1, \quad \forall i \in V * \quad (4)$$

$$\sum_{i \in V} x_{it}^{k} - \sum_{j \in V} x_{tj}^{k} = 0, \quad k \in K, t \in V * \quad (5)$$

$$\sum_{j \in V*} q_j \left(\sum_{i \in V*} x_{ij}^{k} \right) \leq Q, \quad \forall k \in K \quad (6)$$

$$x_{ij}^{k} \in \{0, 1\}, \quad \forall i, j \in V, k \in K \quad (7)$$

The objective function in equation (1) is to minimize the total distance travelled by the vehicle. Equation (2) is the decision variable that indicates whether vehicle k travels directly from node i to j. Constraints in equations (3) and (4) ensure that each evacuation node is served at least once by a vehicle. Constraints in equation (5) guarantee the route continuity, and that the same vehicle visits all nodes in the route. Constraints in equation (6) ensure that the total demand of any route must not exceed the capacity of the vehicle. Sign restrictions in equation (7) indicate that x_{ij} is a set of binary variables.

6.4 Study Area and Dataset

The study area in this chapter covers the tsunami-prone area in Phuket, which includes 15 sub-districts. A number of pre-defined evacuation nodes are scattered across the area as illustrated in Figure 6.1. The data of geographic coordinates of both evacuation nodes and the depot are essential for the solution method, and they have been collected from the Department of Disaster Prevention and Mitigation (DDPM), Ministry of Interior, Thailand.

According to Figure 6-1, all evacuation nodes are located in the hazardous areas in which a specific risk level is assumed by the historical data of the tsunami in 2004 that was recorded by the DDPM. The most dangerous areas are defined with risk number 3 which means the areas are most likely to be hit by a 10-metre tsunami surge, while the risk numbers 2 and 1 would have a possibility of smaller impacts, respectively.

Bear in mind that demand in disaster relief can be gauged from the number of affected people. For solving the CVRP model, a number for demand has to be assigned to each evacuation node in order to obtain a routing solution. In this case, a vehicle carries a load of relief bags, each of which contains essential items for survival such as food, water, and medical care. Thus, a relief bag is considered as a unit of demand in this study.

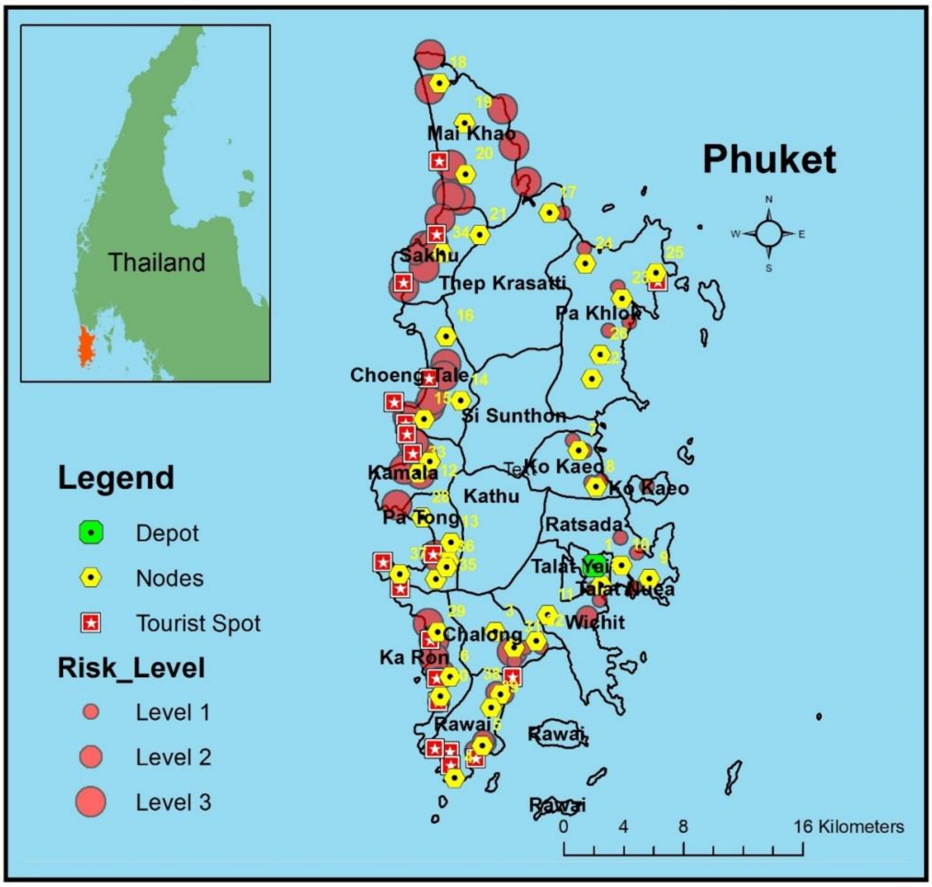


Figure 6-1: The drawing of evacuation nodes across the tsunami-prone area.

As mentioned, the demand data can be derived from the estimates of the affected population. This research separates the affected population into two categories: residents and non-residents (vacationers). The estimates of vulnerable residents are derived from the GIS-based application proposed in the previous chapter, while the tourist data in the study area are directly collected from the Department of Tourism (DOT), Ministry of Tourism and

Sport, Thailand. The overall picture of the data contributing to the CVRP solution is illustrated in Figure 6-2.

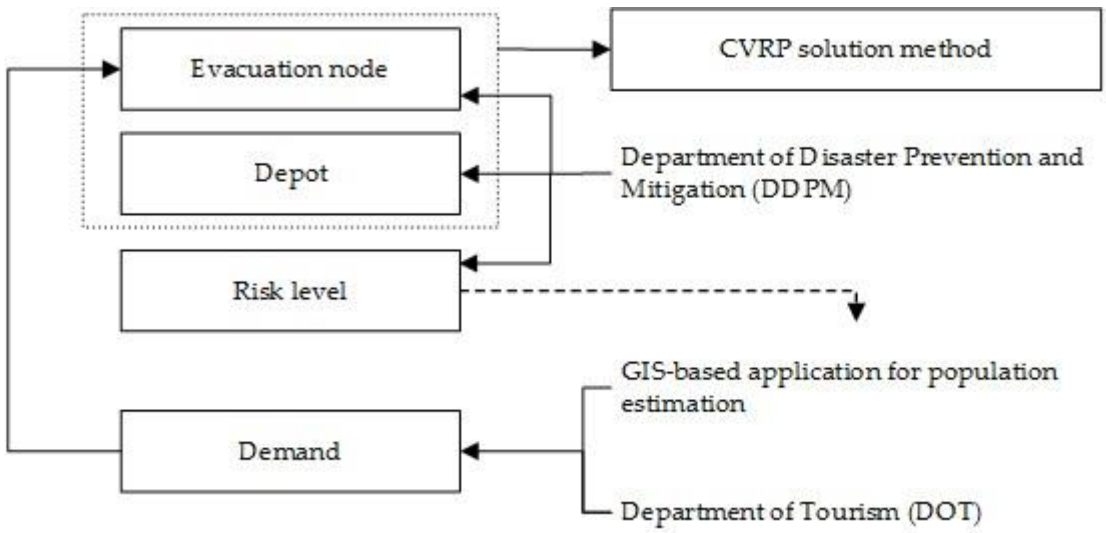


Figure 6-2: Data structures.

The historical data of tourists visited in the study area are collected and statistically analysed as the mean value of a day in each month. For example, if the historical data of vacationers who visited Phuket in January show 1,439,689 persons, the average per day is 1,439,689/31 = 46,442 people. Thus, the rest of the year is conducted in the same manner.

Furthermore, the number of tourists who visit each central attraction in the study area (see Figure 6.1) is surveyed by DOT. Thus, a fraction of the number visiting in each tourist spot and the total number of tourists per day can be calculated. As a result, the weight is distributed to the nearest evacuation node as a vacationer estimation.

6.5 Methodology

In order to solve the CVRP for humanitarian logistics, the solution methods have to be efficiently designed. The overview of the methodology is illustrated in Figure 6-3.

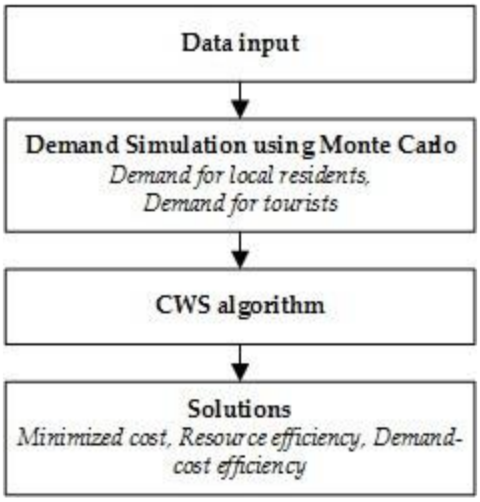


Figure 6-3: Methodology for solving the CVRP.

The method begins with data and parameter input for the problem. Then, the first process is to simulate a set of demands, which is derived from local residents and vacationers, for each node to be an essential component for solving the CVRP model. This chapter proposes the Monte Carlo technique to simulate uncertain demands in the affected area. After obtaining the demand, the CWS heuristic is used for solving the combinatorial optimization in order to gain near-optimal solutions. Furthermore, the solutions include not only transportation cost but also demand-cost efficiency and resource efficiency. The details of solution methods are described in the following section.

6.5.1 Demand Simulation

Demand can be directly converted from the numbers of persons affected. In this study, it is assumed that one victim receives just one relief bag from a supply vehicle. Thus, the number of the affected people in a node is exactly the demand figure for that node. Consequently, the rest of this chapter will use the term *demand* instead of *affected population*.

The total demand for each evacuation node is the sum of residents' and vacationers' demands, each of which is random from the uniform distribution and the normal distribution, respectively. However, a single randomization for each demand may not be meaningful in the aspect of real-world problems. Therefore, after receiving the total demand, this research applies MCS to model the demand repeatedly in order to see all possible outcomes, allowing for better decision making under uncertainty.

6.5.1.1 Randomised demand for local population

Firstly, the GIS-based approach proposed in the previous chapter generates the estimation of a range of minimum and maximum demand in each evacuation node. Demand here is countable and therefore a discrete form of data; thus, when picking a quantity of demand at random from the interval, the probability of its occurring is equally likely. With this sense, Walpole and Myers (1978) claim that the simplest function where the random variable assumes all its values with equal probability is the uniform distribution. If the random variable x assumes the values $x_1, x_2, \ldots, x_k$, with equal probability, then the discrete uniform distribution is given in equation (8).

$$f(x; k) = \frac{1}{k}, \qquad x = x_1, x_2, \ldots, x_k \tag{8}$$

The uniform distribution can be graphically illustrated in Figure 6-4.

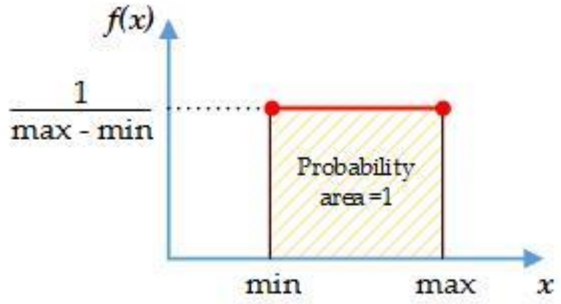


Figure 6-4: The graph of discrete uniform distribution.

Thus, the function of the possible values of x is:

$$(max - min) \times f(x) = 1 \tag{9}$$

$$f(x) = \frac{1}{max - min} \tag{10}$$

As a result, the probability density function of the uniform distribution is:

$$f(x) = \begin{cases} \dfrac{1}{max - min} & for\ min \leq x \leq max \\ 0 & otherwise \end{cases} \tag{11}$$

In order to obtain a random demand from an interval, a random function is used to create a random variable probability u, which is an area under the curve, from the uniform distribution on the interval (0, 1) as shown in the following equation,

$$u = \mathcal{R}(0{,}1), \quad 0 < u < 1, \tag{12}$$

where u = random variable and $\mathcal{R}$ = random function.

An example of generating a random demand X from the interval of minimum and maximum demand resulting from the GIS-based application is illustrated as follows. Firstly, the minimum and maximum demand are denoted as min and max, respectively. Subsequent, a random variable u is generated from the function in equation (13). A random demand X is then generated identically between min and max, as shown in Figure 6-5.

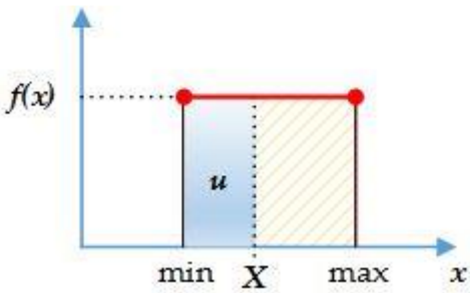


Figure 6-5: Generating a random demand X from a random variable u.

According to Figure 6-5, a random demand X generated from a random variable u is described by replacing X in equation (9):

$$(X - min) \times f(x) = u \tag{13}$$

Substituting the probability density function in equation (11) to equation (13):

$$(X - min) \times \frac{1}{max - min} = u$$

Thus: $$X = min + (max - \mathrm{min}) * u \tag{14}$$

After obtaining the function of random demand X in equation (14), an experiment is conducted with the threshold scenario solution addressed in the previous chapter, which is shown here in Table 6-1. In this experiment, 20 trials of random variable u are generated from equation (12) in order to attain a set of random demands.

Scenario	Parameter				Numerical solution		
	Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)	Evac. node	Min. affected	Max. affected
Threshold	$s = 10$	$b = 0.5$	$u = 50$	$p = 95$	1	572	1,747
					2	1,005	4,705
					3	3,521	5,193
					4	1,463	2,393
					5	2,540	4,476
					6	236	908

Table 6-1: Threshold scenario solution (extracted from chapter 5).

According to Table 6-1, if the evacuation node 1 is taken as an example, the interval demand is defined: $min = 572$, and $max = 1747$. Therefore, a random demand is obtained by substituting the min-and-max value in equation (14):

$$X = 572 + (1747 - 572) * u \tag{15}$$

By drawing a random variable u in equation (15) repeatedly, a set of randomised demand X generated can be graphically observed in Figure 6-6.

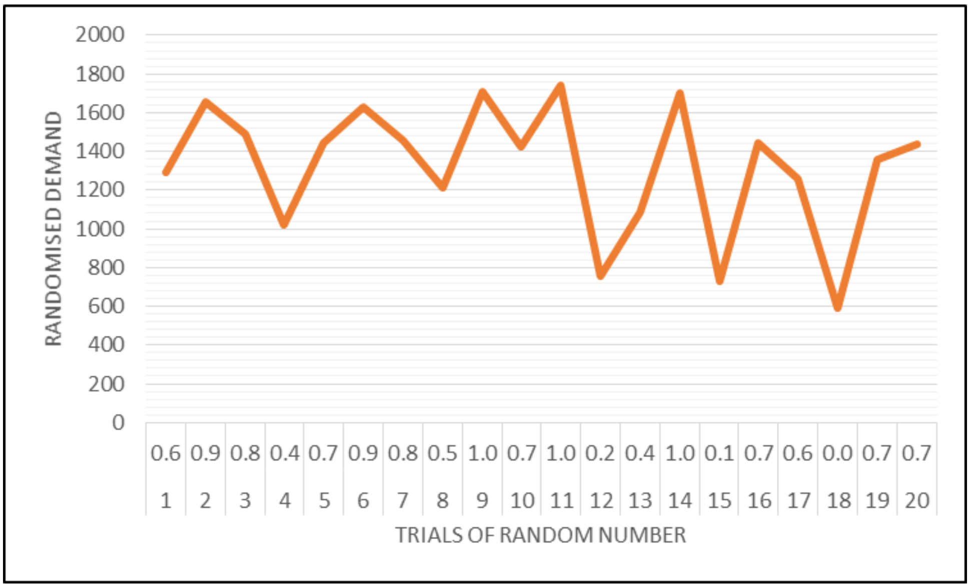


Figure 6-6: Trial results of randomised demand from uniform distribution.

As can be seen from Figure 6-6, the overall values of randomised demand fluctuate greatly between *min* and *max* numbers. As a result of 20 trials, the smallest number of the randomised demand is 591 in the 18st trial; nevertheless, in the 11th test, the random value hits the peak of 1740. Thus, within this event, every time a random variable is drawn the outcome is difficult to predict due to its uncertain nature. As a result, using a single randomness may not be appropriate for quantitative analysis in the real-world application.

As this research uses the term *demand* instead of *population*, as described earlier, it is essential to consider an interesting viewpoint given by Wu *et al*. (2005) that the input data of population such as census and administrative record is based on people's home address, rather than where they work or travel during the day or if they are out of town. This factor can lead to inaccurate population estimation that, in turn, can result in incorrect demand assessment. As a result, this research presents an approach to downscaling the outcomes to predict the demand which is most appropriate for a time of a day such as daytime or nighttime. It can be simply assumed that people tend to go out for work in commercial areas in the daytime and stay home at night. For example, the coastal area in Phuket has a much higher daytime population than that reported by the census. During daytime, not only are tourists around the oceanfront, but more local population are also present in the area due to the economic aspect. Thus, if a tsunami happens in the daytime, it is most likely that there would be more affected people than at nighttime.

In order to facilitate decision making regarding uncertain demand caused by time of day, equation (14) is modified by giving a power of decision parameter d to the random function in equation (12). The new equation is then,

$$X = min + (max - \min) * u^{d}, \quad d \in R^{+} \; and \; d \neq 1 \tag{16}$$

where X = random demand, u = random function, and d = decision parameter.

When using the same instance in Table 6-1, a set of decision parameters is randomly given in Table 6-2, in order to test equation (16).

	1	2	3	4	5	6	7	8	9
Decision parameter (*d*)	0.05	0.12	0.34	0.97	1.20	2.25	3.00	5.20	9.00

Table 6-2: Random number of decision parameters.

According to equation (16), each time variable u is randomly picked from the uniform distribution, a random demand X is recorded. The results of 10 trials, then, are illustrated in Figure 6-7. The overall trend shows that the decision parameters can impact the outcomes in the reverse direction: the smaller d given, the larger X is generated.

However, each trial is done with a single iteration of variable u while changing values of the decision parameter. As a result, Figure 6-7 still shows a great oscillation in randomised demand for each trial. With this problematic occurrence, this research applies MCS to model a distribution of all possible outcomes. Iterating random sampling to generate simulated data is a much more realistic way to deal with value uncertainty in practical analysis and decision making.

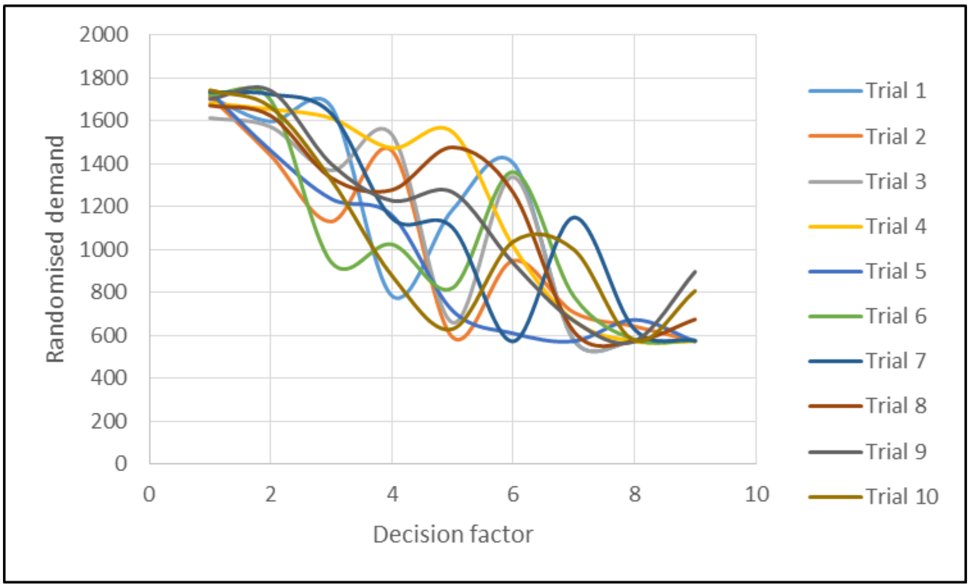


Figure 6-7: Randomised demand using decision factor.

In order to model a distribution of randomised demands, once the GIS-based application generates the estimates of minimum and maximum demand in each evacuation node in the study area, a single demand will be selected at random based on a given decision parameter, and reserved for totalling to another piece of demand obtained from the tourist side. The MCS is then applied to model the final demand for each evacuation mode.

6.5.1.2 Randomised demand for vacationers

Phuket is one of the world's most popular tourist spots due to its magnificent towns and beaches. It is reported that there have been increasing numbers of people travelling to visit this region, including both Thai and foreigner, as shown in Figure 6-8.

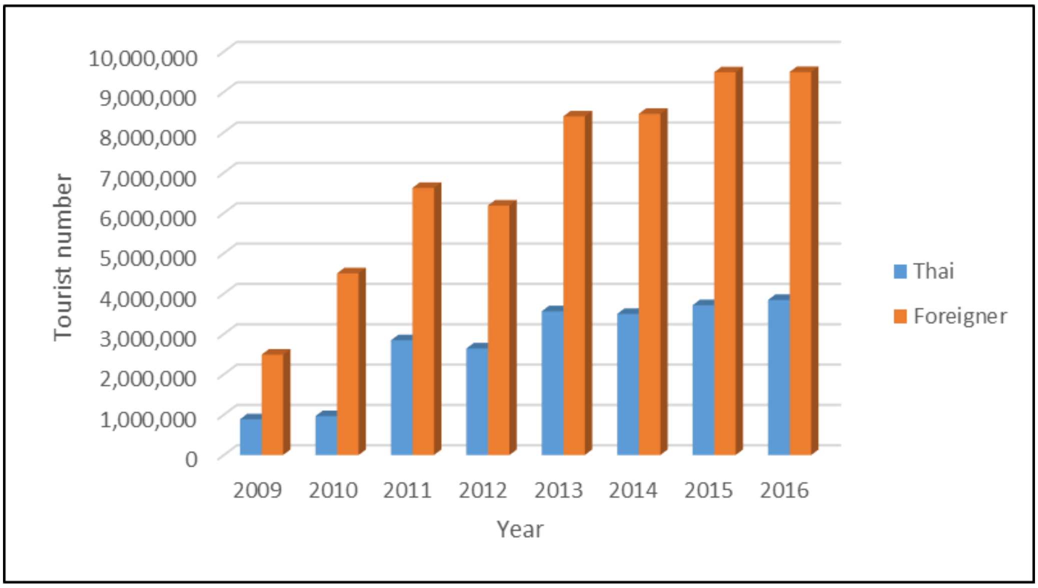


Figure 6-8: Numbers of tourists visiting Phuket between 2009 and 2016.

Source: Department of Tourism, Ministry of Interior Thailand

In the 2004 tsunami event, about 995 foreign vacationers in Phuket were affected, accounting for just under one half of the total number affected, according to the Ministry of Interior of Thailand. Therefore, this research takes tourist numbers into account when estimating the population affected by tsunami inundation.

As data on tourists visiting a place can be measured on the basis of frequency, the tourist numbers are normally distributed. Thus, a demand in this case is selected at random from the normal distribution. If Y is a random demand that has a normal distribution with μ and σ, mean and standard deviation, it can be denoted as $Y \sim n(\mu, \sigma)$. The density function of the normal random demand Y with mean and standard deviation is:

$$n(y; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(1/2)[(y-\mu)/\sigma]^2}, -\infty < y < \infty \tag{17}$$

Therefore;

$$Y = Z\sigma + \mu \tag{18}$$

As the entire area under the normal curve equals one, a normal random variable Z also follows a random function,

$$Z = \mathcal{R}(0,1), \quad 0 < Z < 1 \tag{19}$$

where Z = random variable and $\mathcal{R}$ = random function.

In order to randomise a demand, the mean and standard deviation have to be determined from the normal distribution based on the historical data of vacationers. To experiment with the randomness, a real-case instance from a tourist spot in the study area is taken as an example of finding a random demand.

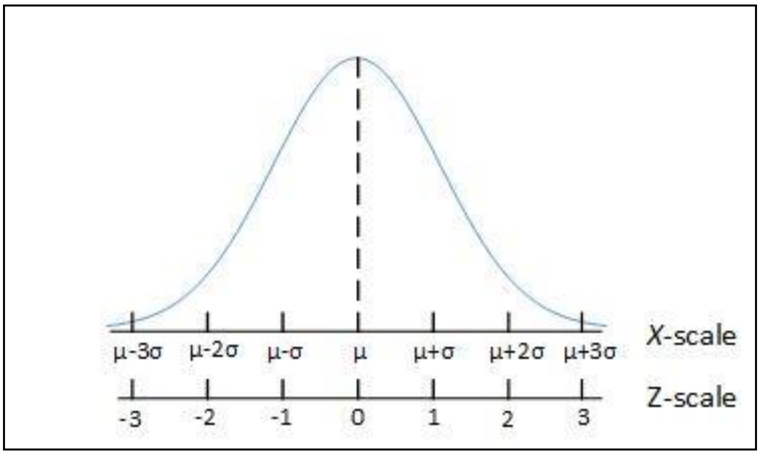


Figure 6-9: Change of scale to standard units.

Source: Freund and Simon, 1997

According to a set of historical tourists visiting the study area, mean and standard deviation can be obtained. For example, suppose a tsunami attacks Karon, one of the finest beaches in the study area, and there is an evacuation node which is a safe place for gathering the affected people in this area. The tourists who visited Karon beach over the last 5 years averaged 317 people per day, with a standard deviation of 75. Assuming that the tourist numbers visiting Karon beach are normally distributed, the normal random variable Z is repeatedly random based on the function in equation (19). Then, the random demand Y is calculated by using equation (18). Finally, the results of 20 trials are generated to observe the distribution of the randomised demand.

Figure 6-10 shows the results of the trials that are mostly distributed in the area between one standard deviation below the mean and one standard deviation above the mean. This means that the outcomes of Y are mostly scattered near the mean value regardless of how many times the random variable Z is drawn. This may not be consistent with the real situation because the statistics of the tourists visiting the study area show that large or small tourist numbers depend significantly on the time of year.

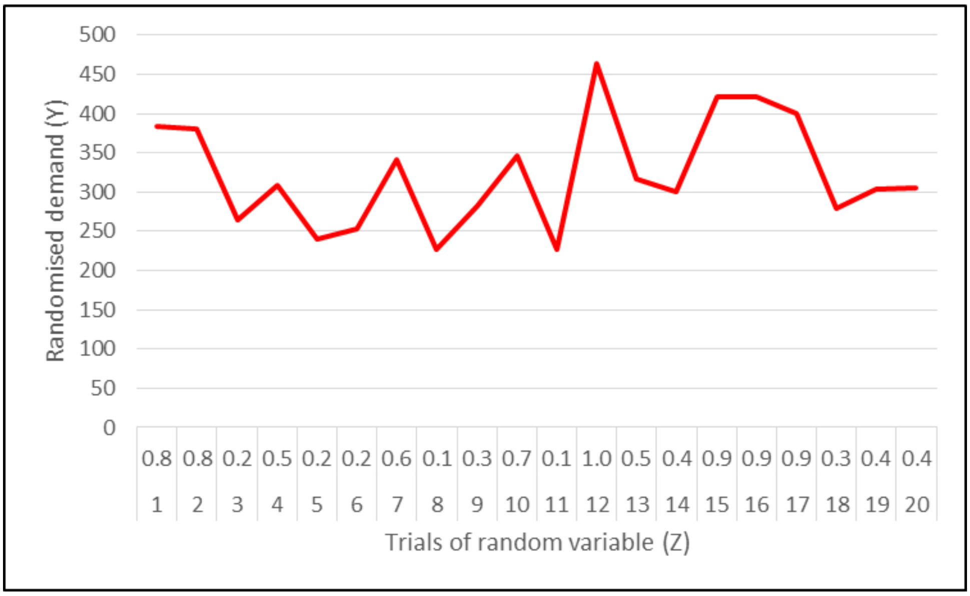


Figure 6-10: Trial results of randomised demand from normal distribution.

Figure 6-11 demonstrates the trend of vacationers visiting Thailand between 2013 and 2016. It can be seen that the number of tourists visiting Thailand each year reflects the seasonal pattern. The numbers increased gradually in the first half of a year, and hitting its lowest level in June. Afterward, there was a steady rise of tourist figures between July and August before a small dip in September. Nevertheless, the figures dramatically increased after that until the end of the year. This repetitive pattern of tourists visiting also applies to the study area, Phuket.

Therefore, if a tsunami occurs, the level of demand for relief aid to be served at a node, which usually fluctuates near the mean value, is not applicable.

This is because demand is most likely to be above the mean during the high tourist season, while below the mean during off-peak travelling season.

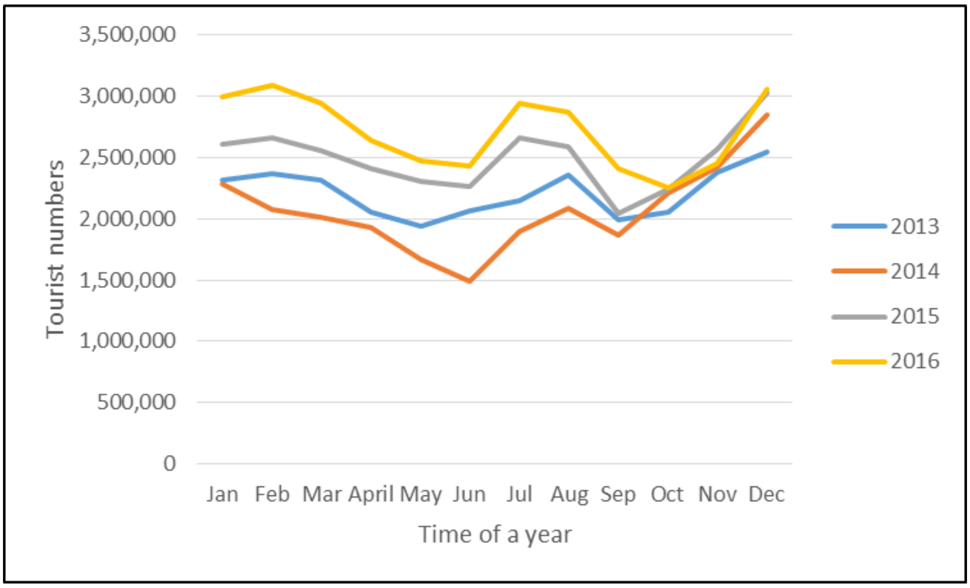


Figure 6-11: Overall trend of tourists visiting Thailand between 2013 - 2016.

Source: Department of Tourism, Ministry of Tourism and Sport, Thailand.

To fix this issue, a random variable Z must be restricted to a suitable range of probability. For instance, as shown in Figure 6-12, a probability variable Z is limited to vary between μ and $\mu + 3\sigma$ for finding a random demand if a tsunami occurs during the peak tourist season. Then, the random demand Y will fall somewhere above the mean. In contrast, if a tsunami attacks the study area during the off-peak tourist season, a variable Z has to be randomly restricted between $\mu - 3\sigma$ and μ; consequently, a point of demand Y would be located on the x-axis below the mean. This implies that the peak and off-peak tourist seasons can be used as a decision parameter to model a distribution of randomised demand.

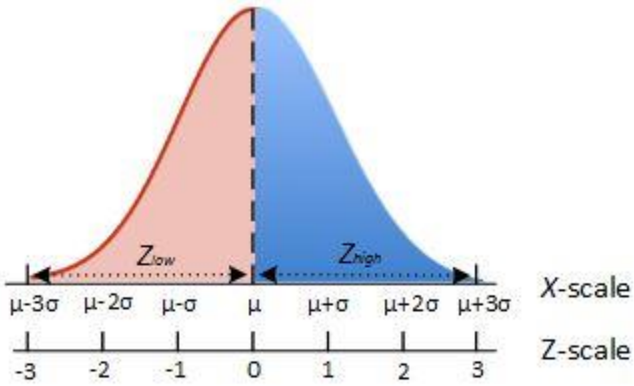


Figure 6-12: Control of random variable for peak and off-peak tourist season.

The example of the evacuation node in Karon beach is tested for the proposed approach by using a decision parameter of high and low tourist seasons, in the case of an occurrence of a tsunami. Also, the mean of 317 and the standard deviation of 75 are taken for this experiment. Table 6-3 contains the data of value Y and probability variable Z of the Z scores between +3 and -3. Thus, the random function is proposed to generate a random variable Z during the peak and off-peak tourist seasons.

$$Z = \begin{cases} \mathcal{R}(0.5,1), & \text{if peak travelling season} \\ \mathcal{R}(0,0.5), & \text{otherwise} \end{cases} \tag{20}$$

The normal random variable Z is repeatedly random using a function based on the decision parameter in equation (20). Then, the random demand Y is calculated by using equation (18). Finally, the results of 20 trials are generated for each decision parameter in order to observe the distribution of the randomised demand, as shown in Figure 6-13.

Z score	value Y	probability Z	Z score	value Y	probability Z
3	542	0.9987	0	317	0.5000
2.9	535	0.9981	-0.1	310	0.4602
2.8	527	0.9974	-0.2	302	0.4207
2.7	520	0.9965	-0.3	295	0.3821
2.6	512	0.9953	-0.4	287	0.3446
2.5	505	0.9938	-0.5	280	0.3085
2.4	497	0.9918	-0.6	272	0.2743
2.3	490	0.9893	-0.7	265	0.2420
2.2	482	0.9861	-0.8	257	0.2119
2.1	475	0.9821	-0.9	250	0.1841
2	467	0.9772	-1	242	0.1587
1.9	460	0.9713	-1.1	235	0.1357
1.8	452	0.9641	-1.2	227	0.1151
1.7	445	0.9554	-1.3	220	0.0968
1.6	437	0.9452	-1.4	212	0.0808
1.5	430	0.9332	-1.5	204	0.0668
1.4	422	0.9192	-1.6	197	0.0548
1.3	415	0.9032	-1.7	190	0.0446
1.2	407	0.8849	-1.8	182	0.0359
1.1	400	0.8643	-1.9	174	0.0287
1	392	0.8413	-2	167	0.0228
0.9	385	0.8159	-2.1	160	0.0179
0.8	377	0.7881	-2.2	152	0.0139
0.7	370	0.7580	-2.3	144	0.0107
0.6	362	0.7257	-2.4	137	0.0082
0.5	355	0.6915	-2.5	129	0.0062
0.4	347	0.6554	-2.6	122	0.0047
0.3	340	0.6179	-2.7	114	0.0035
0.2	332	0.5793	-2.8	107	0.0026
0.1	325	0.5398	-2.9	99	0.0019
0	317	0.5000	-3	92	0.0013

Table 6-3: Data of value Y and probability variable Z of the Z score.

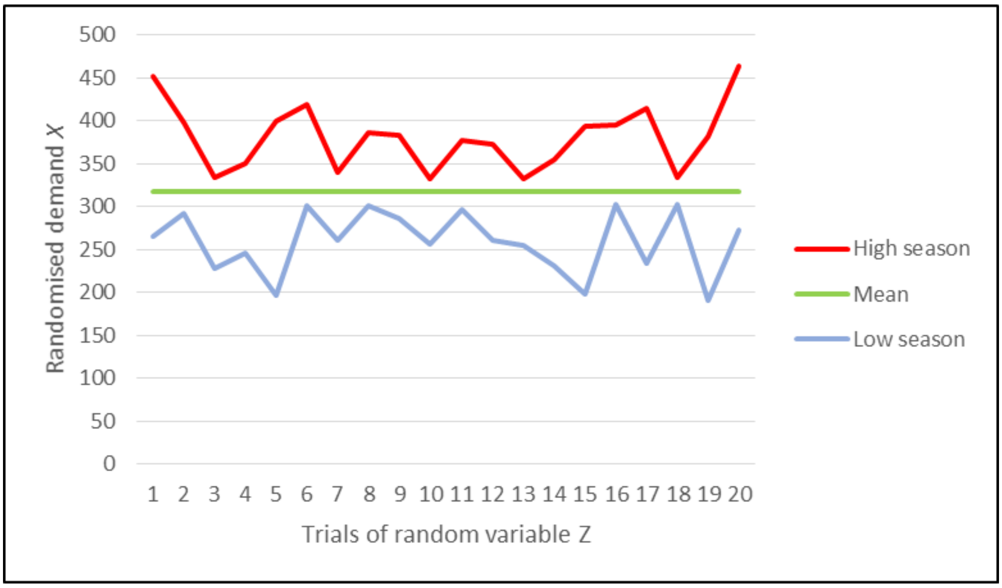


Figure 6-13: Trial results of randomised demand from normal distribution using decision parameter.

As can be seen in Figure 6-13, when randomising variable Z using the decision parameter of the high travelling season, all outcomes of demand Y are distributed over the mean of all trials. While using the low-season parameter, all randomised demand Y fluctuate under the mean. Thus, this approach using a decision parameter to control the distribution of tourist figures is more appropriate than those results shown in Figure 6-10, which ignore the trend of tourists moving into or out of the area. As a result, taking seasonal tourism into account would be more meaningful for the demand estimation in the case of a disaster occurrence.

However, a randomised demand for affected vacationers in each evacuation node has to be summed with another demand, which is also randomly generated from the side of the local population. Then, the processes of randomization are recalculated over and over again (e.g. 10,000 times) to form a distribution of all possible demands. For each iteration, a set of random variables is generated according to the random functions. This approach is widely known as the Monte Carlo technique.

6.5.1.3 The use of MSC for modelling the total demand

During the MCS, demands are sampled at random from a probability distribution. Each set of samples is called an iteration, and the resulting outcome from that sample is recorded. The MCS does the iterative process hundreds or thousands of times, and the result is a probability distribution of possible outcomes in order to ask 'what if' and see the results. This means that the results of a simulation can be analysed by using statistics such as the mean, standard deviation, and percentiles. In this way, the MCS provides a much more comprehensive view of describing uncertainty. As a result of this benefit, this technique is used for generating the total demand of residents and vacationers.

In order to simulate demand for humanitarian logistics in the aftermath of a tsunami, the overall process is illustrated in Figure 6-14. The simulation begins with the input data that consists of a range of demand estimated from the GIS-based application and the tourist data. With respect to the demand of the local population, the population-estimation approach using GIS produces a demand for each evacuation node in the form of a minimum-maximum range. On the other hand, the historical tourist data give the mean and standard deviation for the initial data to generate demand for tourists. The methods of generating randomised demand for each part have been described in sections 6.5.1.1 and 6.5.1.2.

In each node, after the demand for each part is generated based on the decision parameters, they are summed and become the total demand. The MCS then is used to generate the repetitive process, beginning with creating random variables until obtaining the total demand. For example, if the iteration is done 10,000 times, then there is a set of 10,000 possible outcomes of demand. The data of simulated demand is assumed to follow the normal distribution. Therefore, the statistical function is used to produce the most common measure of central tendency that can describe the data.

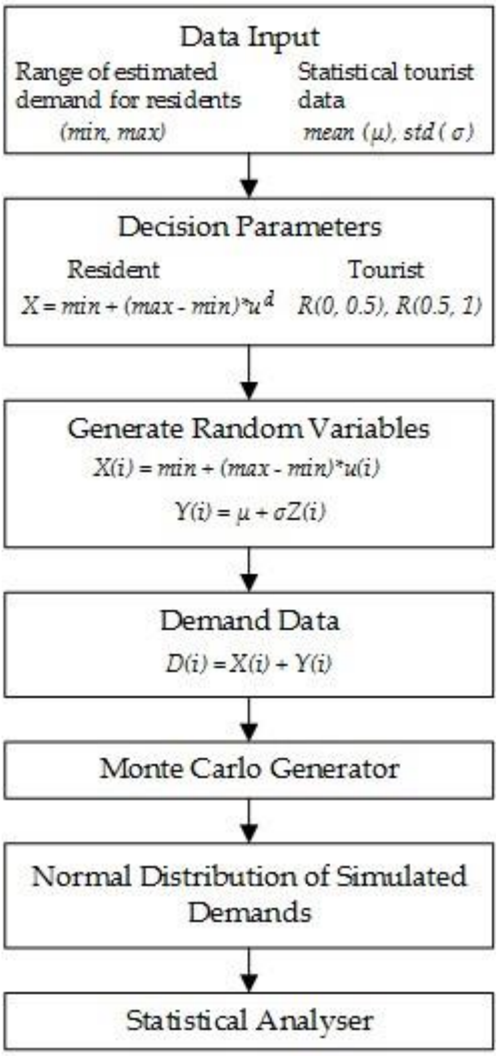


Figure 6-14: The overall process of modelling demand using MCS.

The example of evacuation node 1 in Table 6-1, and the tourist data of Karon beach, are also given by using the MCS with all problem scenarios based on given decision parameters. With five decision parameters of demand for residents and two parameters of demand for tourists, possible situations are illustrated in Table 6-4.

No.	Scenarios (Tourist : Resident)	Demand for tourist and decision parameter		Demand for resident and decision parameter	
1	$t_l : r_1$	Low season (t_l)	$\mathcal{R}(0,0.5)$	Very low impact (r_1)	d = 9
2	$t_l : r_2$				
3	$t_l : r_3$			Low impact (r_2)	d = 3
4	$t_l : r_4$				
5	$t_l : r_5$			Medium impact (r_3)	d = 0.97
6	$t_h : r_1$	High season (t_h)	$\mathcal{R}(0.5,1)$		
7	$t_h : r_2$			High impact (r_4)	d = 0.34
8	$t_h : r_3$				
9	$t_h : r_4$			Very high impact (r_5)	d = 0.05
10	$t_h : r_5$				

Table 6-4: Problem scenarios based on decision parameters of demands.

When using the demand range of evacuation node 1 (min = 517, max = 1714), as shown in Table 6-1, and the data of tourists at Karon beach that has the average 317 people per day, with the standard deviation of 75, the process of modelling demand in Figure 6-14 is applied with the iteration of 10,000 times for the simulation by using the Monte Carlo generator. After the iteration, in each scenario, the mean is calculated from the distribution of all possible outcomes of the demand. The simulated demand for each scenario is illustrated in Figure 6-15.

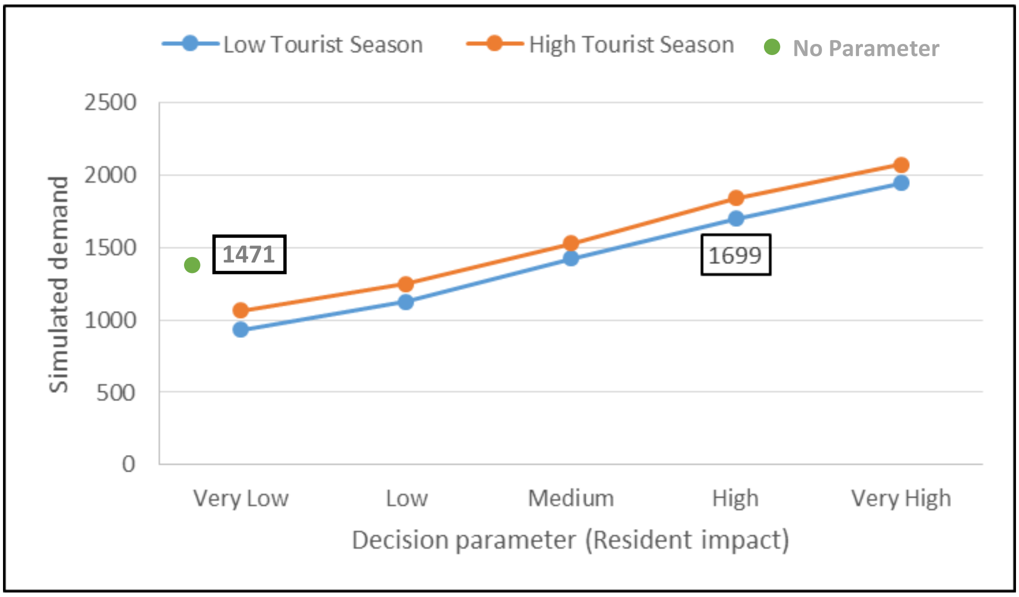


Figure 6-15: Simulation results of 1,000 iterations of each problem scenario.

As can be seen from Figure 6-15, if no decision parameters are considered, the simulated demand of node 1 shows about 1,471, regardless of whether people are travelling during the day and of whether the trend of tourists visiting the area is increasing or decreasing. In contrast, applying decision parameters for both sides can give more meaningful results. For example, if a tsunami occurs in daytime during the low tourist season, the decision maker may have to choose the level of impact on the local residents that is most likely to happen (e.g. very high, high, or even medium), depending on the situation on that day; also, the off-peak travelling parameter is chosen according to the current tourist season. Thus, the demand for this node is simulated with the scenario of low tourist season – high impact on residents, for example. The result of demand simulated by this scenario shows about 1,699 items (see Figure 6-15). By doing this for all evacuation nodes, the numerical results of simulated demand are then distributed to all nodes, and are used later as essential data of the CWS algorithm for solving the CVRP model.

6.5.2 The CWS heuristic for solving the CVRP

The CVRP belongs to the class of NP-hard problem; for that reason, the exact methods become highly time-consuming as the problem instances increase in size. This research proposes a solution method to solve the CVRP by using the CWS heuristic. The CWS is one of the best-known heuristic algorithms, which has been widely applied in many combinatorial optimization problems. The CWS is probably one of the most cited and successful heuristics for solving VRPs (Laporte *et al.*, 2000; Juan *et al.*, 2011). It has been proven as an efficient constructive heuristic. The main feature of the algorithm is that it is able to able to take distance saved into account, i.e. if two customers, who are served independently, are instead served by one delivery vehicle, savings occur. This implies that this heuristic method is based on an estimation of savings from merging routes.

Clarke and Wright (1964) proposed a savings method for solving VRP with more than one vehicle, which became the most popular heuristic algorithm for the VRP. The basic savings concept addresses the cost savings obtained by joining two routes into one route, as illustrated in Figure 6-16, where location 0 represents the depot.

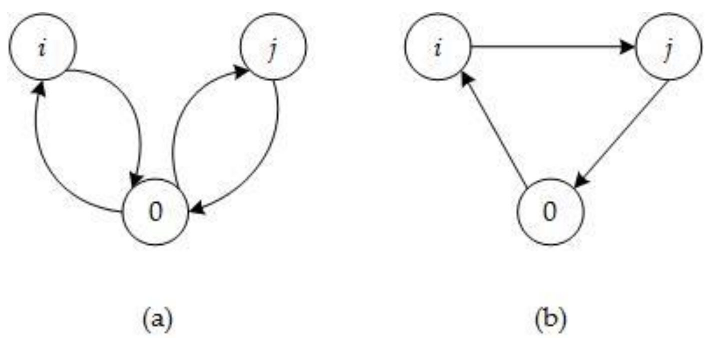


Figure 6-16: Illustration of the savings concept.

Initially in Figure 6-16 (a), nodes *i* and *j* are visited on separate routes. An alternative to this is to visit the two nodes on the same route, for example, in the sequence *i* – *j*, as illustrated in Figure 6-16 (b). Because the transportation costs are given, the savings, which result from driving the route in Figure 6-16 (b) instead of the two routes in Figure 6-16 (a), can be calculated. Denoting the transportation cost between two given nodes *i* and *j* by C_{ij}, the total cost D_a in Figure 6-16 (a) is:

$$D_a = C_{0i} + C_{i0} + C_{0j} + C_{j0} \tag{21}$$

Equivalently, the transportation cost D_b in Figure 6.16 (b) is:

$$D_b = C_{0i} + C_{ij} + C_{j0} \tag{22}$$

By combining equation (21) and (22), the savings S_{ij} is obtained:

$$S_{ij} = D_a - D_b = C_{i0} + C_{0j} - C_{ij} \tag{23}$$

Relatively large values of S_{ij} indicate that it is attractive, with regard to the costs, to visit nodes *i* and *j* on the same routes such that node *j* is visited immediately after node *i*.

The overall procedures of the savings algorithm are illustrated in Figure 6-17. In the first step of the savings method, the savings for all pairs of nodes are calculated by using equation (23), and all pairs of nodes are sorted in descending order of the savings. Subsequently, from the top of the sorted list of node pairs, one pair of nodes is considered at a time. When a pair of nodes *i* – *j* is considered, the two routes that visit *i* and *j* are combined, if this can be done without deleting a previously established direct connection between two nodes, and if the total demand on the resulting route does not exceed the vehicle capacity.

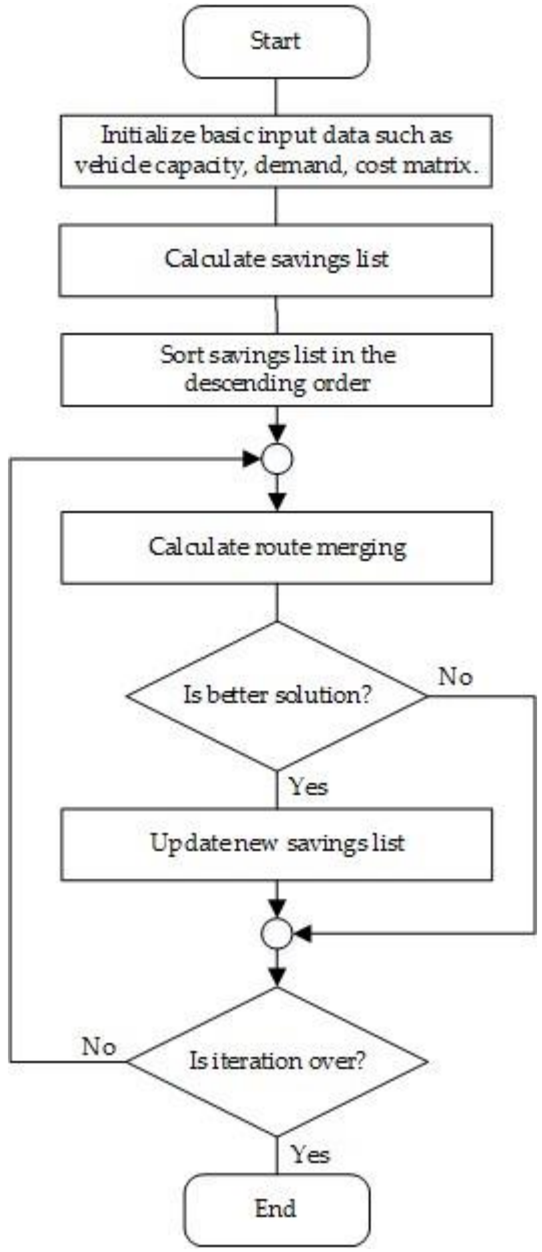


Figure 6-17: The algorithm of the CWS.

Nonetheless, a node demand could be greater than the vehicle capacity in the real-world application, especially in disaster relief when demands are unexpectedly large. This is the problem in which at least one node j has a demand q_j > vehicle capacity Q, making the vehicle not able to satisfy the demand by visiting the node only once. In order to keep the constraint, the delivery quantities of each route do not exceed the vehicle capacity Q; validated, this research proposes an algorithm to create an initial phase before calculating the savings. The algorithm is to select nodes with unsatisfied demand for initializing a route. Then, the residual capacities, which are the difference between unsatisfied demand and the vehicle capacity, are shared between the routes.

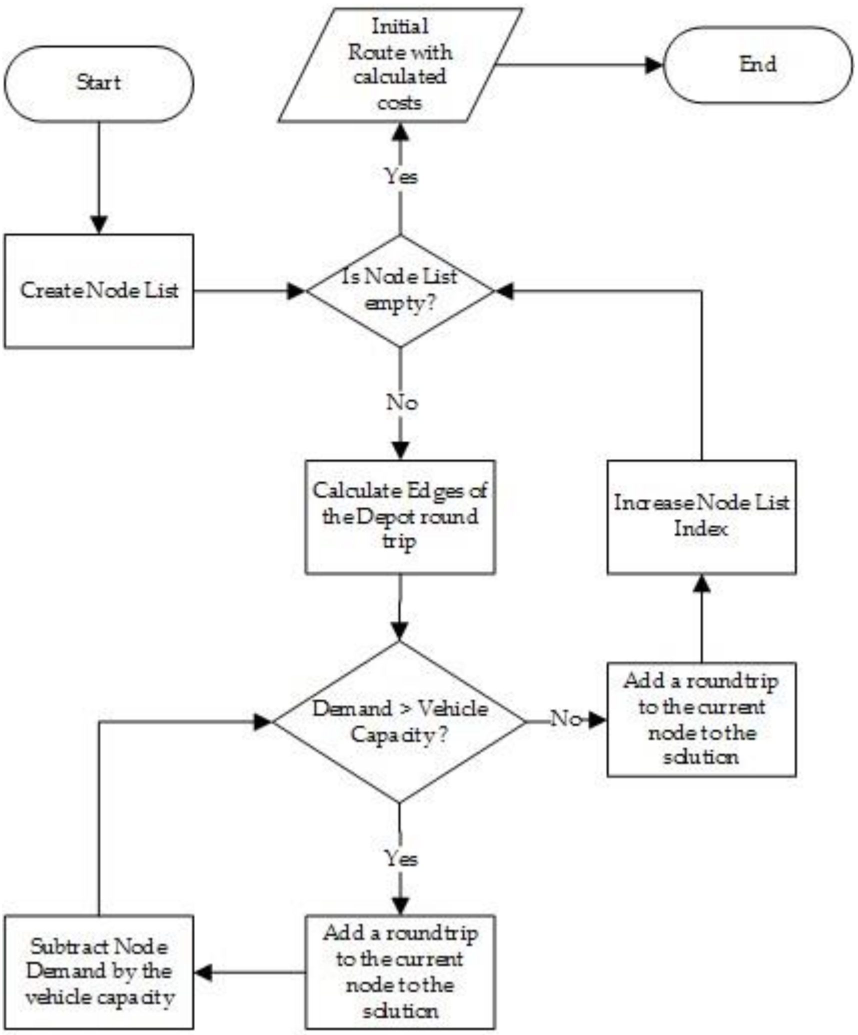


Figure 6-18: The algorithm of creating initial routes.

After determining nodes with unsatisfied demand and sharing remaining capacities, the cost is initially calculated between the depot and each node list. As a result, the initial routes produce the total cost D_a in equation (21). This cost is then used as a contribution of the CWS algorithm. The proposed algorithm of creating initial routes is shown in Figure 6-18.

6.5.3 Additional solutions

It is worth noting that the numerical solutions produced by the CWS heuristic not only encompass a set of routes with the least travel cost, but also the resource efficiency and the demand-cost efficiency. This is because in a disaster situation transportation resources are usually restricted (Balcik *et al.*, 2008; Ichoua, 2010). By using the notation in section 6.3, the resource efficiency and demand-cost efficiency can be estimated by equations (24) and (25) respectively. Besides the minimized cost, the algorithm of creating both efficiencies is illustrated in Figure 6-19,

$$resource\ efficiency = \left(min \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}^{k} \right) \times \left(\frac{1}{K \times S \times T} \right) \quad (24)$$

$$demand - cost\ efficiency = \left(\sum_{j \in V*} q_j \right) \times \left(\frac{1}{\sum_{(i,j) \in A} c_{ij} x_{ij}^{k}}, k \in K \right) \quad (25)$$

where K = number of vehicles, S = average vehicle speed, and T = operation time.

In equation (24), the resource efficiency is estimated by the fraction of total cost minimized and the planned transportation resource, which is the multiple of vehicle numbers, average vehicle speed, and time desired for the operation deadline. The resource efficiency determines whether the current resources being used or to be used are sufficient to achieve the desired deadline. The ratio under one indicates that the planned resources would be adequate for the preferred operation deadline. Otherwise, the decision maker may have to make an increase in either vehicle numbers or speed of the vehicles, or both.

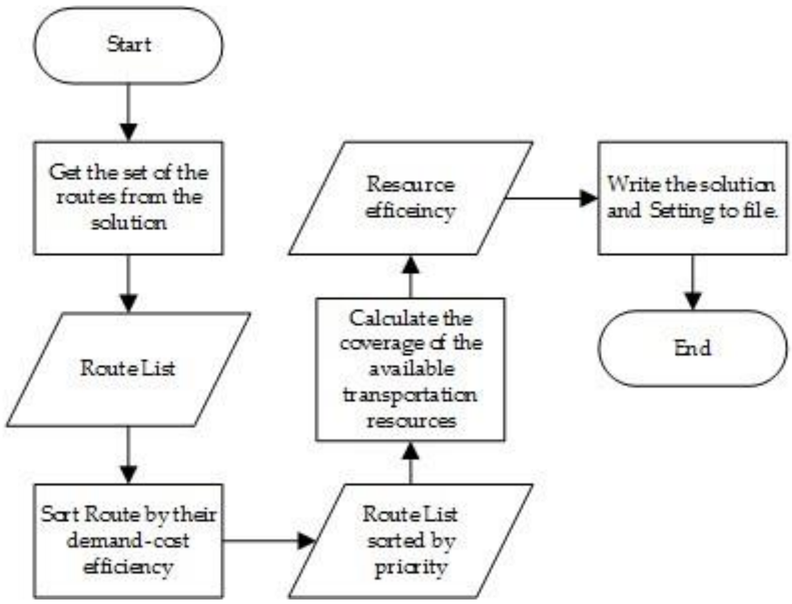


Figure 6-19: The algorithm of creating resource efficiency and demand-cost efficiency in the solution.

In the case when transportation resources are really restricted, the decision maker may have to make a decision on route priority. Equation (25) explains that a route with high demand while having low cost implies high priority. Thus, a route with greater value of demand-cost efficiency should logically receive a higher level of concern in case of inadequate resources. In other words, a route that can serve relief items to a larger number of affected people with lower cost gets greater priority.

Furthermore, the solutions show a list of priority routes in descending order. Each route solution includes cost, simulated demand, demand-cost efficiency, and a set of nodes visited by a vehicle in that route.

6.6 Experimental Results

This section studies the CVRP with simulated demand and a quantity of demands to be served in each evacuation site depending on the given seasonal parameters. Hence, the 10 problem scenarios in this section are based on seasonal parameters such as those shown in Table 6-4. The real instances of 38 evacuation locations and the supply centre (DDPM Regional Office No. 18, Phuket) are used as demand and supply nodes, respectively, for solving the CVRP model.

This experiment is conducted for the case that a tsunami, which is assumed to have the same characteristics as the 2004 tsunami, attacks the study area. A Java implementation is used to obtain the solutions through the entered data. The following data are required to perform the CVRP model that the CWS heuristic is used to solve.

Firstly, the affected population data in each evacuation node is required for CVRP optimisation. This data is obtained through estimates developed using the 2004 tsunami data documented by the DDPM. Thus, the altitude of the tsunami wave that was observed in each Phuket coastal town, as illustrated in Table 6-5, are used to determine how many people would be affected. By using the GIS-based application, the development of which is described in Chapter 5, the affected population numbers in each evacuation location are estimated as shown in Table 6-6.

No.	Sub-district	Parameter			
		Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)
1	Pa Tong	8	0.1	50	0.90
2	Karon	8	0.1	50	0.95
3	Rawai	7	0.1	50	0.95
4	Kamala	7	0.1	50	0.95
5	Choeng Tale	8	0.1	50	0.95
6	Sakhu	9	0.1	50	0.95
7	Mai Khao	8	0.1	50	0.90
8	Chalong	5	0.1	50	0.95
9	Wichit	3	0.1	50	0.95
10	Ratsada	3	0.1	50	0.95
11	Ko Kaew	2	0.1	50	0.95
12	Pa Khlok	2	0.1	50	0.95
13	Thep Kasatti	7	0.1	50	0.90

Table 6-5: Proposed scenario for estimating affected population.

Sub-district	Node ID	Position		Affected population	
		Longitude	Latitude	Minimum	Maximum
Wichit	2	98.39797	7.877127	18	294
Chalong	3	98.33349	7.848805	43	107
Rawai	4	98.30895	7.7601	55	488
Rawai	5	98.32591	7.779708	213	574
Ka_Ron	6	98.30614	7.82144	451	1,478
Ko Kaeo	7	98.38404	7.958663	12	28
Ko Kaeo	8	98.39456	7.93669	78	489
Ratsada	9	98.4273	7.881151	32	915
Ratsada	10	98.41034	7.889198	458	1,648
Wichit	11	98.36556	7.858907	18	914
Kamala	12	98.29357	7.951735	210	830
Pa Tong	13	98.30668	7.90293	42	403
Choeng Tale	14	98.31235	7.988928	250	665
Choeng Tale	15	98.29015	7.977677	685	1,772

Table 6-6: Numerical results generated from the GIS-based application for estimating affected population.

Sub-district	Node ID	Position		Affected population	
		Longitude	Latitude	Minimum	Maximum
Thep Krasatti	17	98.36607	8.102743	285	1,074
Mai Khao	18	98.299	8.181258	629	1,015
Mai Khao	19	98.31454	8.157153	102	554
Mai Khao	20	98.31521	8.126065	284	1,338
Sakhu	21	98.32371	8.089471	23	81
Pa Khlok	22	98.39218	8.002173	14	45
Pa Khlok	23	98.41033	8.051021	26	124
Pa Khlok	24	98.38802	8.071925	65	119
Pa Khlok	25	98.43097	8.066483	125	844
Pa Khlok	26	98.39727	8.016927	32	193
Pa Tong	27	98.29745	7.880589	2,118	3,426
Pa Tong	28	98.28912	7.918085	36	623
Ka Ron	29	98.2987	7.848446	728	1,611
Ka Ron	30	98.30033	7.80956	23	276
Chalong	31	98.34516	7.839167	402	768
Chalong	32	98.35867	7.843133	502	1,094
Kamala	33	98.28675	7.944947	454	1,665
Sakhu	34	98.30103	8.078223	122	436
Pa Tong	35	98.30535	7.891249	1,422	2,859
Pa Tong	36	98.30386	7.887848	1,026	1,652
Pa Tong	37	98.27555	7.883423	55	407
Rawai	38	98.33678	7.810617	39	214
Rawai	39	98.33132	7.802781	35	223

Table 6-6: Numerical results generated from the GIS-based application for estimating affected population (Continued).

In addition, assumptions of the threshold input variables for transport resource management are shown in Table 6-7.

Input variable	Value	Unit
Number of trucks	1	vehicle
Vehicle capacity	5,000	relief items (bags)
Average speed of vehicle	60	km/hr
Desired operation time	8	hr

Table 6-7: Threshold input variables for transportation resource management.

With respect to the seasonal parameters in Table 6-4, the problem scenarios can be categorised as shown in Table 6-8.

Scenario	Seasonal parameter tourist : resident	Possible Interpretion
1	Low season (t_l) : Very low impact (r_1)	Tourist season is off-peak, very few locals are travelling such as in a late nighttime.
2	Low season (t_l) : Low impact (r_2)	Tourist season is off-peak, few locals are travelling such as in an early nighttime.
3	Low season (t_l) : Medium impact (r_3)	Tourist season is off-peak, moderate locals are travelling such as in a daytine during off-working hours.
4	Low season (t_l) : High impact (r_4)	Tourist season is off-peak, large number of locals are travelling such as in a daytine during peak-working hours.
5	Low season (t_l) : Very high impact (r_5)	Tourist season is off-peak, very large number of locals are travelling such as in a daytine with social activities.
6	High season (t_h) : Very low impact (r_1)	Tourist season is peak, very few locals are travelling such as in a late nighttime.
7	High season (t_h) : Low impact (r_2)	Tourist season is peak, few locals are travelling such as in an early nighttime.
8	High season (t_h) : Medium impact (r_3)	Tourist season is peak, moderate locals are travelling such as in a daytine during off-working hours.
9	High season (t_h) : High impact (r_4)	Tourist season is peak, large number of locals are travelling such as in a daytine during peak-working hours.
10	High season (t_h) : Very high impact (r_5)	Tourist season is peak, very large number of locals are travelling such as in a daytine with social activities.

Table 6-8: Problem scenarios based on the seasonal parameters.

Moreover, the statistical data of tourists, based on 2016 records, for each evacuation location are shown in Table 6-9, and the symmetric cost matrix extracted from the Phuket map is shown in the Appendix F.

Evacuation node	Tourist spot	Mean	Standard deviation
3	Ao Chalong	434	102
4	Ao Sane	316	75
4	Nai Han Beach	1107	261
4	Ya Nui Beach	790	187
5	Rawai Beach	316	75
6	Kata Beach	1581	373
12	Kamala Beach	317	75
12	Lam Singh Beach	790	187
14	Bang Tao Beach	632	149
15	Pansea Beah	474	112
15	Surin Beach	632	149
20	Mai Khao Beach	316	75
21	Nai Yang Beach	790	187
25	Ao Po	1301	307
27	Freedom Beach	1440	340
29	Karon Beach	1880	444
30	Kata Noi Beach	1107	261
31	Ao Chalong	867	205
32	Ao Chalong	650	154
33	Kamala Beach	317	75
34	Nai Thon Beach	316	75
35	Patong Beach	711	168
36	Patong Beach	711	168
37	Paradise Beach	632	149

Table 6-9: Tourist statistical data assigned to evacuation node.

In each scenario, when a tsunami occurs, the logistics manager must make a decision based on the seasonal parameters. The decision will be based on whether the current tourist season is in peak or off-peak season and the time of day. The numerical solutions of scenario 1 to scenario 10 are illustrated in the tabular format in the Appendix G.

Each solution table shows the number of routes generated with the total minimum cost. For each route, the solution includes its cost, total demand served by the vehicle, demand-cost efficiency and evacuation nodes visited by the vehicle which starts and ends at node 1, which is the depot (DDPM Regional Office No. 18, Phuket).

The priority value of each route is marked in accordance with its demand-cost efficiency. The greatest priority implies that a large number of affected people can be served on the route with the lowest cost used. The other priorities are sorted in descending order of demand-cost efficiency.

The resource efficiency ratio can be interpreted by using 1 as the criteria. If the ratio is less than 1, the current transportation resources are sufficient for the operation within the desired time. On the other hand, if the ratio is greater than 1, the current transportation resources are insufficient for the operation within the preferred time.

According to the solutions in all problem scenarios, it is obvious that the seasonal parameters significantly affect the solutions. In any tourist season, the total cost, which is directly proportional to the number of routes generated, changes in accordance with the given time of day.

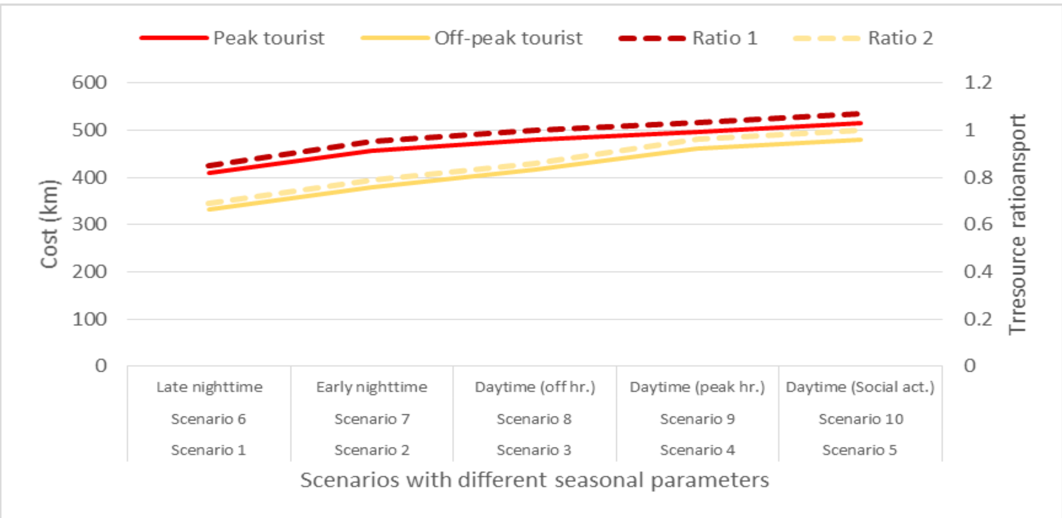


Figure 6-20: Comparing the numbers affected between high and low travelling seasons.

The solutions of the total cost with different input parameters during the off-peak tourist season are shown in Figure 6-20. For instance, if a very low impact on locals is given (e.g. tsunami occurs late at night), the total cost is about 332 kilometres, while for a very high impact parameter (e.g. tsunami occurs during a peak daytime hour), the total cost jumps to about 480 kilometres. There is approximately a 45% increase in the number people affected from scenario 1 to scenario 5.

The solutions of the total cost with different input parameters in peak tourist season also are shown in Figure 6-20. For example, if a very low impact on locals is given (e.g. tsunami occurs late at night), the total cost is about 409 kilometres, whereas, if a very high impact parameter (e.g. tsunami occurs during a peak daytime hour) is selected, the total cost considerably increases to about 515 kilometres. The number of affected people increases from scenario 6 to scenario 10 by about 26%.

Also, the total cost and transport resources used are directly proportional to the total distance generated. In any tourist season, the trends of total cost and transportation resources are changed following the same pattern. For instance, during the off-peak tourist season, the total cost and transportation resources used are 332.54 and 0.69, respectively, in scenario 1 (very low impact on local residents). Nevertheless, the total cost and transportation resources used in scenario 5 (very high impact on local residents) significantly increase to 480.40 and 1.00, respectively. In the peak tourist season, increasing the impact level on local residents will result in higher total cost and transportation resources used than those during the low tourist season. The total cost and transportation resources used are 408.84 and 0.85, respectively, in scenario 6 (very low impact on local residents), but in scenario 10 (very high impact on local residents), they dramatically rise to 515.39 and 1.07, respectively.

The investigation of the solutions show that the seasonal parameters in terms of both tourist season and time of day can affect the cost of operating relief logistics. The number of tourists in and out of Phuket especially can be inferred to be an important decision factor to manage the transportation resources so they are adequate for humanitarian logistics if a tsunami occurs.

6.7 Chapter Summary

This chapter solves the CVRP with simulated demand for humanitarian logistics. The classical CWS algorithm is used for solving the CVRP model. The feature of the problem is to model the demand by using Monte Carlo Simulation. A tsunami with the worst-case severity is assumed to attack the study area, Phuket, Thailand. The real-case instance of the area is then used to test the problem scenarios for finding a set of relief routes with the minimum transportation cost.

In each evacuation location, the demands are modelled in two parts: one for the local population, another one for vacationers. A range of resident demand is derived from the GIS-based application for estimating the population affected by tsunami; the demand from the range is then randomly derived from the uniform distribution. On the other hand, the quantity of demand from tourists is randomly determined from the normal distribution, which is based on the historical data of travellers visiting the area. The randomised demand from two parts is summed as the total demand and allocated to the evacuation node. The procedure of demand randomness is repeatedly simulated by using the Monte Carlo generator to attain a distribution of demand solutions from which a final demand is used in the CWS algorithm.

In addition to generating routes for delivering relief items for the affected people, the solutions encompass resource efficiency and demand-cost efficiency to estimate the transportation resources used and the priority route, respectively. The resource efficiency may help the decision maker to manage transportation factors such as number of vehicles and vehicle speed to achieve the logistic operation within the deadline period. If the logistic resources are limited, the decision maker may use the demand-cost efficiency to determine route priority for serving the affected population.

The solutions, however, disregard service time such as loading/unloading time. Thus, it should be noted that a decision of resource management that refers to the resource efficiency must be used carefully, because the outcome does not take service time into consideration.

Moreover, in case of unlimited logistic resources, demand-cost efficiency may not be considered because all evacuation locations should be served simultaneously in order to have delivery impartiality for the people suffering from the disaster. However, a situation of infinite resources has rarely happened for first-aid assistance in the aftermath of a disaster. Thus, the decision maker can utilise the proposed algorithm for planning and managing humanitarian relief logistics before and during the disaster response phase as the experiments show an average of solution time approximately 150 milliseconds, which is very quick for obtaining a solution.

Chapter 7: The Integration of GIS and CVRP for DSS

7.1 Introduction

Over the past few years, undersea earthquakes and subsequent tsunamis have received global attention as natural threats to coastal countries. Recent examples of the most destructive tsunamis are the Indian Ocean tsunami in 2004 and the Japanese tsunami in 2011. Tsunamis can greatly devastate an area and physically affect not only life but also community infrastructure such as property and service facilities. As a result, immediate needs such as food, water and basic medical supplies are urgently needed for the casualties' survival.

A good logistic preparedness for delivering relief items from the supply centre to a set of demand locations is critical for saving lives. Thus, distributing vehicles in an efficient manner to the areas affected by a tsunami is an important approach in humanitarian logistics. A good logistics plan needs a good distribution technique, however, and it would be best if such an efficient technique could be combined with state-of-the-art technology.

Among the numerous information technology applications being used in the logistics sector, Geographic Information Systems (GIS) is one of the most powerful and effective tools. A GIS is a computer system for capturing, storing, analysing and displaying data related to positions on the Earth's surface. The system can include the data concerning population, infrastructure, terrain, and so on. Once all of the desired data have been entered into the system, they can be combined to produce a wide variety of individual maps. Moreover, the GIS can present descriptive information of the data on the maps (Akay *et al.*, 2008; Gumusay and Sahin, 2009; Wing *et al.*, 2010). Thus, the GIS is a valuable tool that provides decision-making support for many areas of planning and operations. It has proven its efficiency in various areas of study by solving different kinds of problems in the multitude of application domains which made it so popular and widespread (Krichen *et al.*, 2014).

The GIS has some weaknesses, however. One big challenge is that it cannot fully serve the optimization aspect of distribution problems, nor can optimization result in visualization (Tlili *et al.*, 2013). To utilize the feature from the two perspectives, the GIS must be merged with the optimization. Optimization offers various tools that can widely contribute to improving GIS performance while tackling and solving more complicated problems (Li *et al.*, 2011) as well as in multi-criteria decision making (Malczewski, 2006).

This research focuses on combining two systems that belong to different areas of study to strengthen the efficiency of the whole system as a decision support system (DSS). Integrating a GIS and an optimization tool as a DSS can be addressed as a GIS-O (Faiz and Krichen, 2013; Krichen *et al.*, 2014). An overview of three main integration strategies has been proposed in the literature, namely full, loose and tight integration (Krichen *et al.*, 2014; Tlili *et al.*, 2013). A close analysis, such as the one performed by Faiz and Krichen (2013), shows that selecting the appropriate strategy is dependent on the application. Among the wide spectrum of domains that may be linked to GIS, this research aims to study the class of transportation problems, particularly the Capacitated Vehicle Routing Problem (CVRP), as an issue relevant to both combinatorial optimization and distribution management in a disaster situation.

To this end, this research proposes a tight integration of GIS and CVRP optimization that manages data from a geographical database (GDB) and allows the solution to a problem to be plotted on a map. The decision to opt for the tight integration approach to building a GIS-based DSS was motivated by the sharing of data in the linked system, resulting in a reduced cost and short integration time. Moreover, this approach is recommended for its considerable flexibility, promoting the free selection of models to be combined and their exchangeability when required. Specifically, the tight integration approach starts by extracting distances between each pair of nodes from the GDB, then computing the cost matrix. All such data constitute inputs for the optimization step used to generate a routing plan which will be visualized in a cartographic format showing the itinerary. By using the tight strategy, the routing plan generated from the optimization can be used as the GBD in the GIS environment.

In this study, a spatial DSS was proposed by coupling the GIS to the Clarke and Wright Saving heuristic (CWS) algorithm to handle the CVRP and generate numerical solutions as well as geographical results. The purpose of the GIS-based DSS is to facilitate decision making for planning and managing the CVRP for humanitarian logistics, or basically to design a set of routes to deliver relief items via a visualization map. The solutions also include a decision support feature for the transportation resources (e.g. vehicle number, speed, capacity) being used for the planned routes, and subsequently route sequences in accordance with priority in case transportation resources are limited. Furthermore, the system enables the decision maker to use the Network Analyst in the ArcGIS platform to adjust routing solutions, if necessary. A real-case instance in Phuket was studied to test the proposed DSS.

7.2 Literature Review

Several studies have examined the application of a DSS to determine optimal routing or placement of response fleets travelling to an area along a road network. Most studies found in the literature, however, served a commercial purpose. For example, Basnet *et al*. (1996) proposed a stand-alone application to establish milk collection routes between farmers and dairy facilities in New Zealand. This routing problem comprised a multi-depot CVRP that was solved using a heuristic method on a cluster-first, route-second approach. Similarly, Weigel and Cao (1999) integrated a GIS and a set of optimization algorithms as part of a system to manage two routing problems at a major American retailer. The system used an insertion heuristic to generate an initial solution, which later was improved using a tabu search algorithm. Another study, Nussbaum *et al*. (1997), developed a DSS to solve a complex fuel transportation problem for a Chilean company. In this study, the routes planned for fuel distribution were constrained by tanker capacity, shift durations, delivery time windows and client allocation. This DSS differed from other studies in that it based its decision module on compiled historical expert knowledge rather than optimization techniques. More recently, Faulin *et al.* (2005) presented a DSS for solving a routing problem at a frozen food company in Spain. The DSS was designed to allow for distribution of products from the depot in the city to many customers in different towns. After comparing the solutions of real-world instances obtained with different construction heuristics and a mixed integer program, this study implemented the saving heuristic.

In addition to a DSS for commercial applications, reports in the literature have included implementations of DSS to solve routing problems for public utilities. For instance, Wunderlich *et al.* (1992) presented a DSS solution for routing meter readers at the Southern California Gas Company. Likewise, Ghose (2006) developed a GIS-based DSS to construct a set of routes for collecting waste in India, and Jung *et al.*, (2006) described the design and implementation of a DSS for planning mail delivery and pickup routes for the Korean post office. More recently, Ray (2007) introduced a web-based DSS for designing routes to move oversize and overweight vehicles through state highways in Delaware, USA. Another DSS application was developed for emergency response. Dimopoulou and Giannikos (2004) created a GIS-based DSS to determine how many and what types of firefighting vehicles would be needed to respond to a fire. Vehicle speed capabilities along different road types were considered, as was the critical time in which a vehicle must arrive at a fire to be considered effective.

Despite this large body of research on development of a DSS for vehicle routing and applications for decision making in commercial and public sectors, very limited work has been done on emergency cases, especially implementing a GIS-based DSS for designing routes in tsunami inundations.

To fill this void, this research aims to develop a spatial DSS by integrating GIS and CVRP for humanitarian logistics to facilitate decision making in designing and managing routing plans coupled with other decision support features, including transportation resources and delivery route priority.

7.3 Study Area and Dataset

The Phuket province was the study area for this research. The island lies in the Andaman Sea which is a part of Indian Ocean. It is the largest island in Thailand and the only island big enough to be a province in its own right. The geographic and demographic information of the study area are described in detail in Chapter 4.

Phuket was chosen because its location is at great risk for a future tsunami. The Indian Ocean is home to a number of massive undersea plates which are moving at a regular rate over time. This can cause unpredictable plate collisions. Consequently, there is a high possibility that earthquakes and subsequent tsunamis will hit this area.

The datasets used were used into the DSS application and the ArcGIS platform. For the DSS, three datasets were needed for CVRP optimization: demand data, tourist historical data and distance cost matrix. All these data are in a tabular format. The data in each demand location was automatically produced by the GIS-based application proposed in Chapter 5. The tourist data in each evacuation node, however, had to be manually calculated for the mean and standard deviation according to the historical data. The cost matrix was prepared using the Network Analyst feature in ArcGIS 10.3 software. Moreover, the basemap was used to visualise the study area in the DSS platform. The function of the basemap is to provide background detail necessary to orient the location of the map. Thus, the basemap also enables the decision maker to visualise the overall solutions in terms of a routing map.

In the ArcGIS platform, the datasets used in this case study were in GIS file formats and include digital elevation and administrative boundary data, street footprint data and evacuation location data. The digital elevation data was downloaded at no cost from the USGS Earth Explorer portal in the form of a digital elevation model (DEM), which represents the continuous elevation values over a terrain's surface. For this case study, the DEM, with a resolution of 30 metres, was the product of the Shuttle Radar Topography Mission (SRTM), which is a National Aeronautics and Space Administration (NASA) mission aiming to obtain Earth surface data through remote sensing technology. The availability of SRTM gives users good quality DEMs for performing various types of topographic and elevation analysis.

The administrative boundaries and street footprints were in the format of a vector polygon and a vector line, respectively. These GIS shapefiles were downloaded directly for free from the MapCruzin website, which provides the detailed country-level shapefiles for GIS.

The data for evacuation locations were obtained from the Department of Disaster Prevention and Mitigation (DDPM), Ministry of Interior, Thailand. As a result of the Asian tsunami in 2004, Thai authorities developed tsunami warning systems as well as evacuation plans including evacuation routes and temporary places for evacuees. The evacuation locations are prearranged, utilising local government buildings/areas such as schools, temples and mosques, and other public spaces which are expected to be safe from tsunami flood inundation. To use the data in a spatial analysis, however, the coordinates of the evacuation sites had to be converted to a vector point format in the GIS environment.

All data used in this case study were assessed using ArcGIS 10.3 software. Thus, the ArcGIS platform is an essential component for the data preparation as well as for further operations using Network Analyst, if necessary.

7.4 Methodology

The GIS-based DSS for humanitarian logistics is a system that was designed for a first responder to handle a relief operation in the aftermath of a tsunami. Its main function is to establish vehicle routing plans for distributing goods to fulfil the basic needs of the affected population in the first hours after the disaster event. It includes the GIS-based element for estimating affected population figures, which is linked to the GIS-based module that is designed to optimize vehicle routes to serve the numbers estimated with minimum cost.

The first stage of the system was developed to estimate the number of people affected, based on a set of parameters which depends on the extent of a tsunami. Chapter 5 has a description of this GIS-based application and its methodology.

The second module, which is the logistics optimization, was developed to design a set of routes based on the affected numbers produced earlier. The methodology of the routing problem employed in this module was explained in Chapter 6.

In this DSS context, the affected population in each evacuation location is transformed to demand quantities which are used as an important ingredient for solving the CVRP model. This GIS-based solver also considers seasonal parameters such as the time of day and tourist season to simulate the demand for emergency services as explained in Chapter 6. The main contribution of the DSS system is to help the decision maker effectively manage aid deliveries not only in the planning stage but also in the response phase if a tsunami hits the study area.

Routing solutions are generated in both numerical and geographical formats so that decisions can be facilitated based on the numbers simultaneously with the visualization maps. In addition to the optimization results, the GIS-based DSS also provides two other pieces of assisting information: the transportation resource ratio and the delivery priority in case the transport resources are restricted.

Furthermore, the routing solutions are linked to ArcGIS 10.3 which enables the decision maker to manage real-time routing in the response phase by using the Network Analyst functionality. The architecture of the system is shown in Figure 7-1.

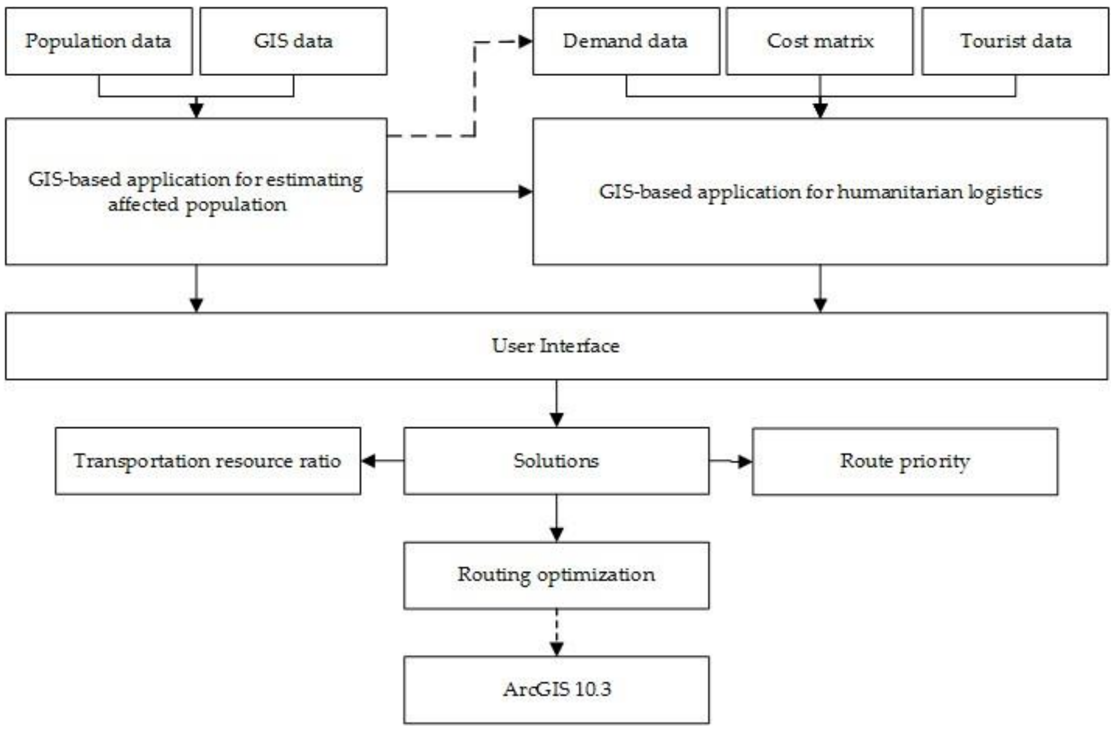


Figure 7-1: Structure of the proposed DSS.

7.5 Development of the GIS-based DSS

The DSS was implemented using Python and Java programming language available in the IntelliJ IDEA Community, which is a Java-integrated, computer development environment. The system enables the decision maker to plan humanitarian logistics in the first hours after a tsunami as well as to quickly correct planned routes for a particular location when roads are unavailable due to tsunami flooding.

The main user interface of the DSS is shown in Figure 7-2. This DSS consists of two modules which are used first to estimate the population affected by a tsunami inundation and second to determine a set of relief routes with a minimum cost. Moreover, the routing results generated by the DSS can be connected to the ArcGIS platform for further visualisation as well as operation through the ArcGIS Network Analyst. The details of each DSS component are now explained.

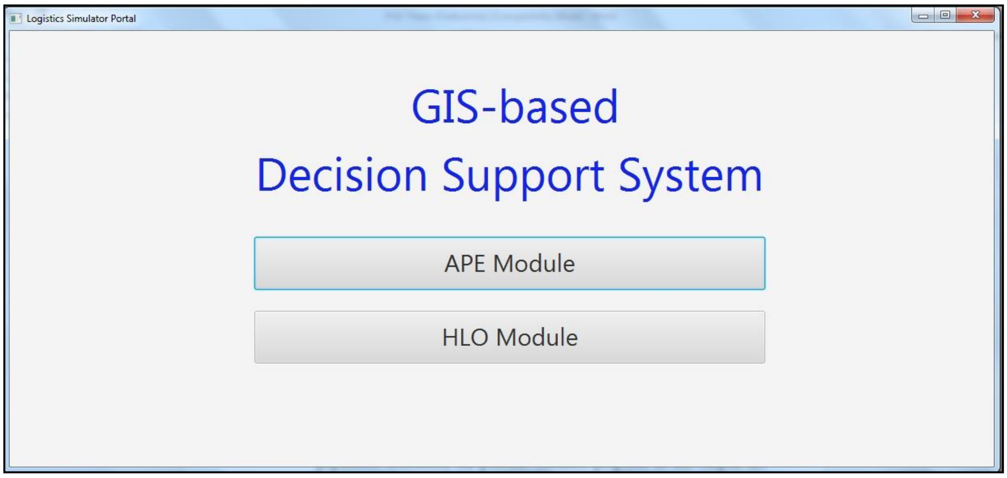


Figure 7-2: The main user interface of the DSS.

7.5.1 Affected population estimation (APE) module

The first module aims to estimate the number of people affected by a tsunami, which is used as a demand quantity in the routing problem environment. To this end, the extent of a tsunami inundation in the study area first is modelled using a set of parameters given by the decision maker. The parameters are subject to the tsunami wave, population and geography of the area. For example, tsunami surge height is obtained according to the altitude of the wave hitting the coastline of a particular area. To evaluate this GIS-based application, a study was carried out earlier (see Chapter 5) and its methodology worked out to demarcate tsunami flood patterns for every metre of surge level rise. Figure 7-3 illustrates the user interface of the Affected Population Estimation (APE).

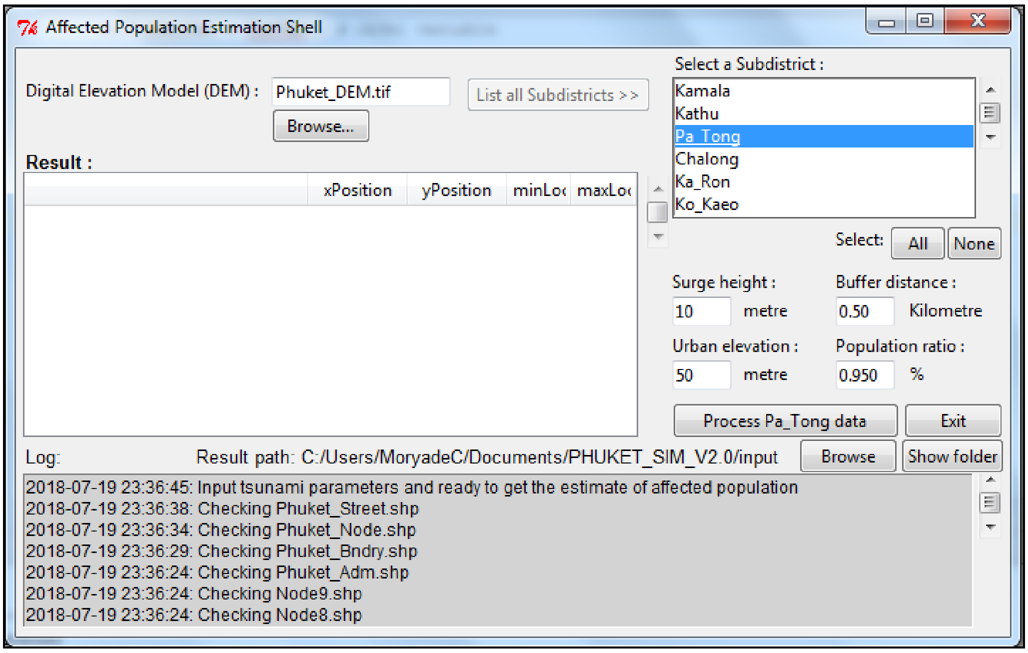


Figure 7-3: The user interface of the first DSS module: affected population estimation (APE).

The APE module was developed using Python programming language. The inundation pattern is based on input parameters such as a DEM, tsunami surge height, buffer distance, urban elevation and population ratio. On the basis of these parameters, the inundation pattern is simulated in accordance with a number of case scenarios, as described in Chapter 5. The tsunami hazard model then is linked to ArcGIS 10.3 and can be visualized over the study area in the ArcGIS platform.

After creating the tsunami hazard model, the APE module produces, with a few clicks, an affected population estimate based on the inundation area. The combination of areal interpolation techniques then is used to present the solutions. Finally, these numerical solutions are interpreted as demand quantities for the next stage, which is the optimization solver for the CVRP.

7.5.2 Humanitarian logistics optimization (HLO) module

The second module was developed to design a set of routes for delivering relief items to the people waiting at each evacuation location. This application was developed using the Java programming language. This module can perform a demand simulation based on seasonal parameters (e.g. time of a day, the tourist season). The user interface of humanitarian logistics optimization (HLO) module is shown in Figure 7-4.

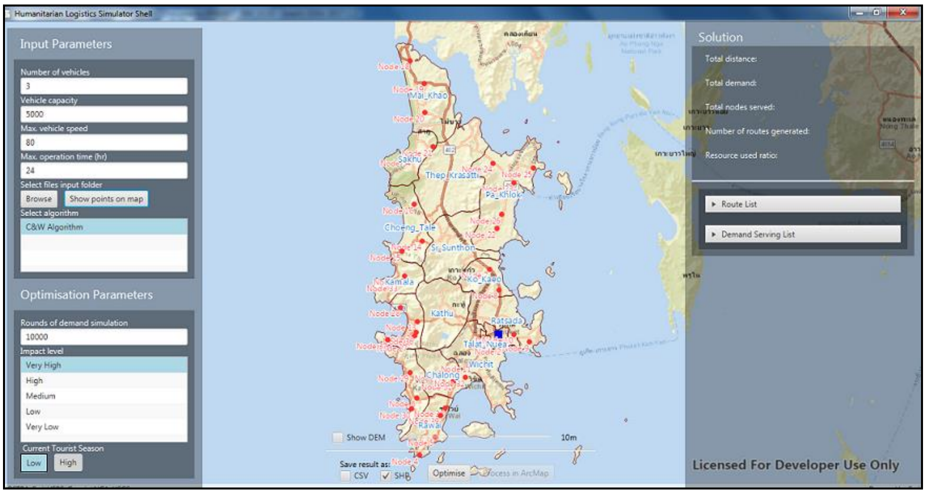


Figure 7-4: The user interface of the second DSS module: humanitarian logistics optimization (HLO).

The HLO works on input parameters related to transportation resources to be used in the relief distribution (e.g. number of vehicles, vehicle capacity, maximum vehicle speed) to meet the desired operation time. Furthermore, to simulate demand, the user can make decisions regarding the tsunami impact level and tourist season, which are based on the time of a day and the current tourist season, respectively. Chapter 6 describes the demand simulation based on seasonal factors.

In the preparedness phase, the HLO runs on those input parameters, determining the routing solutions as well as evaluating a set of transportation resources used for the distribution of relief items. By providing this information, the decision maker can recognise if the input transportation resources are sufficient to complete the operation within the desired deadline. If resources are limited, the module prioritises each route so that the decision maker can manage the deliveries based on those priorities.

The routing solutions are presented both numerically and geographically on the user interface. In addition, there is an option to make routing solutions in the GIS data that can be operated in the ArcGIS platform. Following the plan stage, the decision maker can import the generated GIS files to visualize more details using the ArcGIS Network Analyst and can modify the routing plan in accordance with real-time circumstances during the response phase.

7.5.3 ArcGIS Network Analyst

ArcGIS Network Analyst provides network-based, spatial analysis tools for solving complex routing problems. It uses a configurable transportation network data model, enabling users to solve common network problems. For example, Network Analyst can find the best way to get from one location to another or to visit several locations. The locations can be specified interactively by placing points on the screen, entering an address or using points in an existing feature class or feature layer. If there are more than two stops to visit, the best route can be determined for the order of locations specified by the user.

Once the HLO generates the routing solutions in the form of a point feature class, which represents demand location, the routing plans can be imported to the ArcGIS environment. There the plans can be operated interactively in the ArcGIS platform. Thus, the decision maker can use ArcGIS Network Analyst to perform a visualization and analyse the data in accordance with the situation in real time. For example, if a street in the routing solution is unavailable due to tsunami flooding, the decision maker can use the New Route feature in the Network Analyst to identify the damaged street as shown in Figure 7-5. The Network Analyst then will automatically find a new route for the delivery vehicle, choosing an alternate street based on the shortest path algorithm. Thus, the vehicle can make the delivery and complete the operation as shown in Figure 7-6.

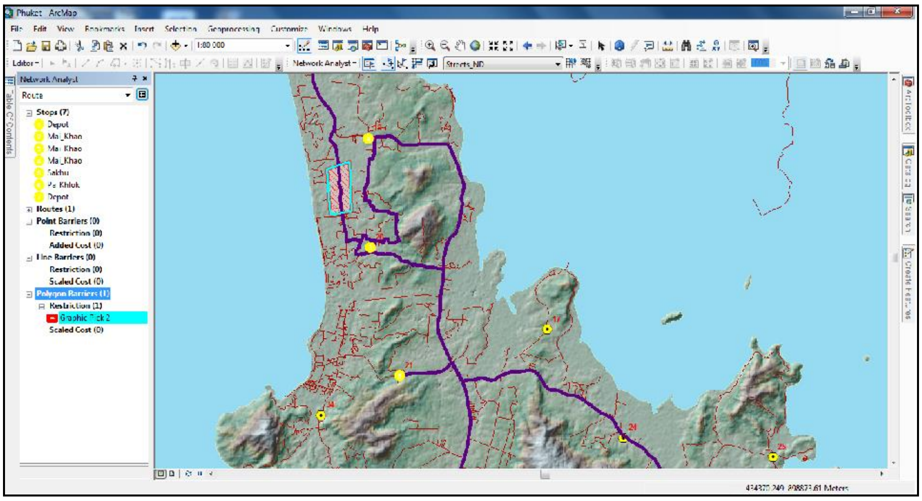


Figure 7-5: A routing solution imported in ArcGIS in the response phase.

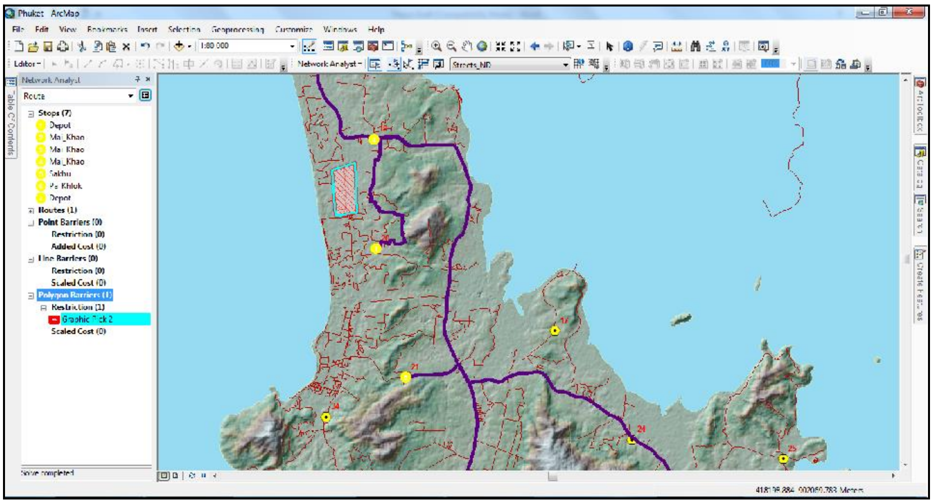


Figure 7-6: Using Network Analyst functionality to avoid a damaged street and automatically find a new one to complete the delivery route.

7.6 Preparedness plan for humanitarian logistics

In disaster management, relief needs to be provided as quickly as possible. Therefore, it is essential to simulate hazardous situations and a relief routing preparedness plan. In this research, an attempt has been made to develop a DSS for tsunami preparedness to find routing solutions for delivering relief items to the people gathering in pre-defined evacuation sites across the area affected by the tsunami inundation.

A preparedness plan for humanitarian logistics is based on a set of problem scenarios according to different multi-parameters models. Regarding population estimation, the problem scenarios proposed in this chapter are taken from the 2004 tsunami that attacked the study area. The DDPM documented the historical data of the tsunami characteristics, i.e. risk level and tsunami wave height in each coastal town.

With respect to routing optimization, the problem scenario proposed in this chapter is identical to the scenario which was numerically investigated in Chapter 6 and was used to establish the routing solutions via the proposed DSS in this chapter. The outcomes in this chapter are in both numerical and geographical formats. As a result, the user can receive a clearer picture of logistics solutions in the planning phase. In addition, the system enables the decision maker to amend the routing plan, if needed, during the response phase.

7.6.1 Proposed scenario on the APE module

To plan relief routes, it is necessary to create a problem scenario from which a number of affected people can be estimated. Hence, this case study is based on the tsunami that hit Phuket on 26 December in 2004. The magnitude of the tsunami wave in each coastal town in Phuket was recorded by the DDPM. Figure 7-7 shows the information of tsunami risk in Phuket and the pre-defined evacuation sites. As the study area is an island encompassed by the sea, the towns adjacent to the coastline would experience different levels of tsunami wave. The towns directly facing the tsunami source are most likely to be hit by higher waves. For example, in the 2004 event, Pa Tong had received the highest tsunami surge of 10 metres, while Rawai was hit by a lower surge of 6–7 metres because it is located far to the southwest of the island (see Figure 7-7). As a result, each coastal town in the island had a different tsunami impact in the 2004 event.

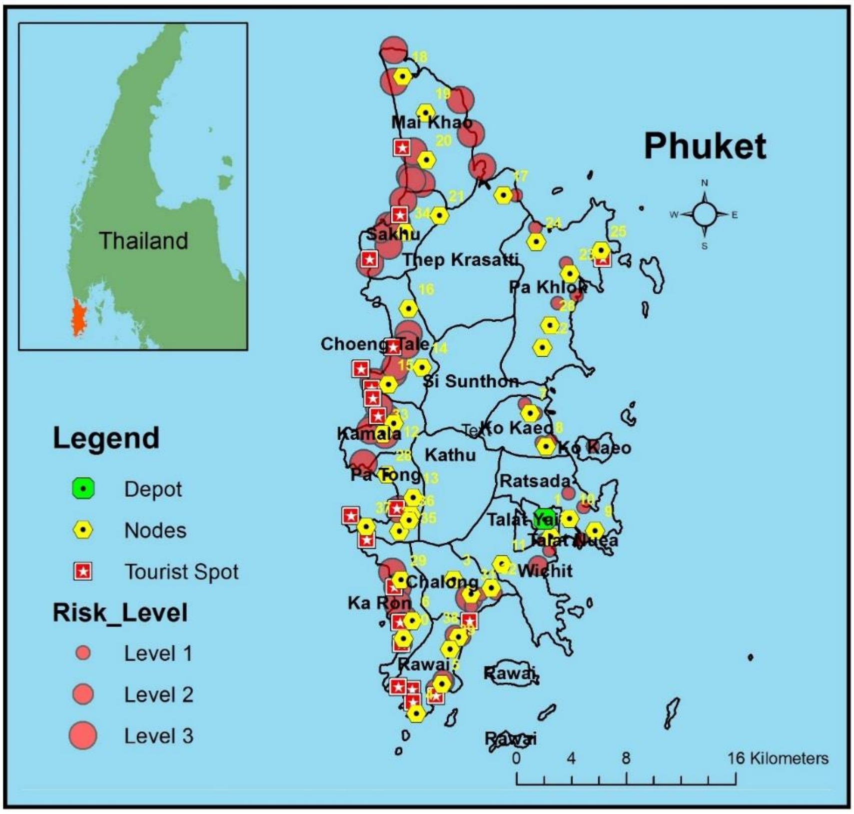


Figure 7-7: Tsunami risk level in Phuket defined by DDPM, Thailand.

According to Figure 7-7, the tsunami risk level is categorised into 3 groups. Each risk level is interpreted as a range of possible tsunami wave height as described in Table 7-1.

Risk level	Tsunami surge height (m)
1	1 – 3.0
2	3.1 – 6.0
3	6.1 – 10.0

Table 7-1: Tsunami risk level.

The risk level and magnitude of the tsunami wave in each coastal town in Phuket were recorded by DDPM as shown in Table 7-2

No.	Sub-district	Risk level	Tsunami surge height
1	Pa Tong	3	8
2	Karon	3	8
3	Rawai	3	7
4	Kamala	3	7
5	Choeng Tale	3	8
6	Sakhu	3	9
7	Mai Khao	3	8
8	Chalong	2	5
9	Wichit	1	3
10	Ratsada	1	3
11	Ko Kaew	1	2
12	Pa Khlok	1	2
13	Thep Kasatti	1	7

Table 7-2: Risk level and tsunami surge height in each town of Phuket.

Within the APE module, each tsunami surge height defined in Table 7-2 was used as a parameter to model the tsunami hazard area in each town. By combining this data with other parameters, a range of affected people in each evacuation location then can be calculated based on the spatial interpolation techniques described in Chapter 5. A set of parameters used in the APE module are assumed according to a document produced by the DDPM. Therefore, this scenario is proposed by using the different parameters given to towns in the study area as illustrated in Table 7-3.

After the parameters for the proposed scenario are entered, the APE generates a range of maximum and minimum affected population for each evacuation site (see Table 7-4). The numerical results produced by the APE will be interpreted as a range of demands in the HLO module. In addition, a demand range in each site will be simulated using the Monte Carlo technique (described in Chapter 6) based on the seasonal parameters.

No.	**Sub-district**	**Parameter**			
		Surge height (m)	Buffer distance (km)	Urban elevation (m)	Pop. ratio (%)
1	Pa Tong	8	0.1	50	0.90
2	Karon	8	0.1	50	0.95
3	Rawai	7	0.1	50	0.95
4	Kamala	7	0.1	50	0.95
5	Choeng Tale	8	0.1	50	0.95
6	Sakhu	9	0.1	50	0.95
7	Mai Khao	8	0.1	50	0.90
8	Chalong	5	0.1	50	0.95
9	Wichit	3	0.1	50	0.95
10	Ratsada	3	0.1	50	0.95
11	Ko Kaew	2	0.1	50	0.95
12	Pa Khlok	2	0.1	50	0.95
13	Thep Kasatti	7	0.1	50	0.90

Table 7-3: Proposed problem scenario on the APES module for estimating affected population.

Sub-district	Node ID	Position		Affected population	
		Longitude	Latitude	Minimum	Maximum
Wichit	2	98.39797	7.877127	18	294
Chalong	3	98.33349	7.848805	43	107
Rawai	4	98.30895	7.7601	55	488
Rawai	5	98.32591	7.779708	213	574
Ka_Ron	6	98.30614	7.82144	451	1,478
Ko Kaeo	7	98.38404	7.958663	12	28
Ko Kaeo	8	98.39456	7.93669	78	489
Ratsada	9	98.4273	7.881151	32	915
Ratsada	10	98.41034	7.889198	458	1,648
Wichit	11	98.36556	7.858907	18	914
Kamala	12	98.29357	7.951735	210	830
Pa Tong	13	98.30668	7.90293	42	403
Choeng Tale	14	98.31235	7.988928	250	665
Choeng Tale	15	98.29015	7.977677	685	1,772
Choeng Tale	16	98.30339	8.027761	232	997
Thep Krasatti	17	98.36607	8.102743	285	1,074
Mai Khao	18	98.299	8.181258	629	1,015
Mai Khao	19	98.31454	8.157153	102	554
Mai Khao	20	98.31521	8.126065	284	1,338
Sakhu	21	98.32371	8.089471	23	81
Pa Khlok	22	98.39218	8.002173	14	45
Pa Khlok	23	98.41033	8.051021	26	124
Pa Khlok	24	98.38802	8.071925	65	119
Pa Khlok	25	98.43097	8.066483	125	844
Pa Khlok	26	98.39727	8.016927	32	193
Pa Tong	27	98.29745	7.880589	2,118	3,426
Pa Tong	28	98.28912	7.918085	36	623
Ka Ron	29	98.2987	7.848446	728	1,611
Ka Ron	30	98.30033	7.80956	23	276
Chalong	31	98.34516	7.839167	402	768
Chalong	32	98.35867	7.843133	502	1,094
Kamala	33	98.28675	7.944947	454	1,665
Sakhu	34	98.30103	8.078223	122	436
Pa Tong	35	98.30535	7.891249	1,422	2,859
Pa Tong	36	98.30386	7.887848	1,026	1,652
Pa Tong	37	98.27555	7.883423	55	407
Rawai	38	98.33678	7.810617	39	214
Rawai	39	98.33132	7.802781	35	223

Table 7-4: Numerical results from the APE module.

7.6.2 Proposed scenario on the HLO module

To attain the geographical solutions on the HLO shell, the datasets needed for the module operation are derived from three sources: the solutions generated from the APE module, tourist statistical data and the distance matrix. These three datasets are in spreadsheet form.

The operation framework for the HLO module is illustrated in Figure 7-8. The framework consists of the datasets, the user interface and the solutions.

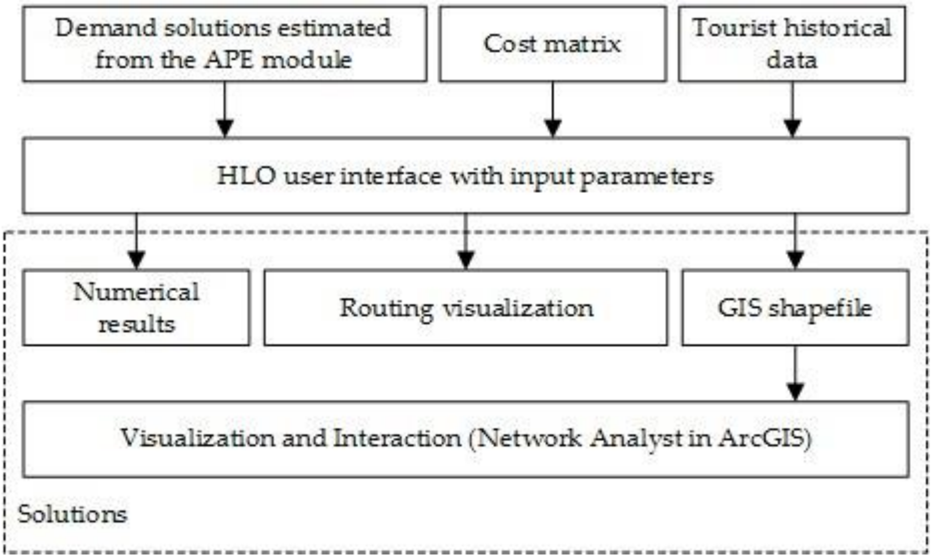


Figure 7-8: HLO framework.

The problem scenarios based on five decision parameters of demand for residents and two parameters of demand for tourists were used to test the system. The possible situations are illustrated in Table 7-5. These scenarios also were studied earlier to test for numerical results (see Chapter 6). In addition to numerical results, the DSS enables the user to assess the solutions in the form of a visualisation map.

No.	Scenarios (Tourist : Time of day)	Seasonal parameter: Tourist	Seasonal parameter: Time of day
1	$t_l : r_1$	Low season (t_l)	Very low impact (r_1)
2	$t_l : r_2$		
3	$t_l : r_3$		Low impact (r_2)
4	$t_l : r_4$		
5	$t_l : r_5$		Medium impact (r_3)
6	$t_h : r_1$	High season (t_h)	
7	$t_h : r_2$		High impact (r_4)
8	$t_h : r_3$		
9	$t_h : r_4$		Very high impact (r_5)
10	$t_h : r_5$		

Table 7-5: Problem scenarios based on seasonal parameters.

As shown in Table 7-5, the problems which are based on given seasonal parameters can result in 10 possible situations. The real instances of 38 evacuation nodes and the relief supply centre (DDPM Regional Office no. 18, Phuket) were used for solving the CVRP model. This experiment was conducted in the case of a tsunami, which is assumed to have the data shown in Table 7-3. Moreover, the input variables for resource management are presented in Table 7-6.

Input variable	Value	Unit
Number of trucks	1	vehicle
Vehicle capacity	5,000	relief items (bags)
Average speed of trucks	60	km/hr
Desired operation time	8	hr

Table 7-6: The input variables for transportation resource management.

The numerical solutions for 10 problem scenarios based on the seasonal parameters in Table 7-5 were illustrated in Chapter 6. In this chapter, problem scenario 1 is proposed to test the GIS-based DSS given the parameters of the low tourist season and very low impact on residents ($t_l : r_1$). According to these parameters, when a tsunami occurs, it is assumed that the tourist season is off-peak, and very few local residents are travelling in the affected area late at night. Figure 7-9 presents the solutions to the proposed scenario.

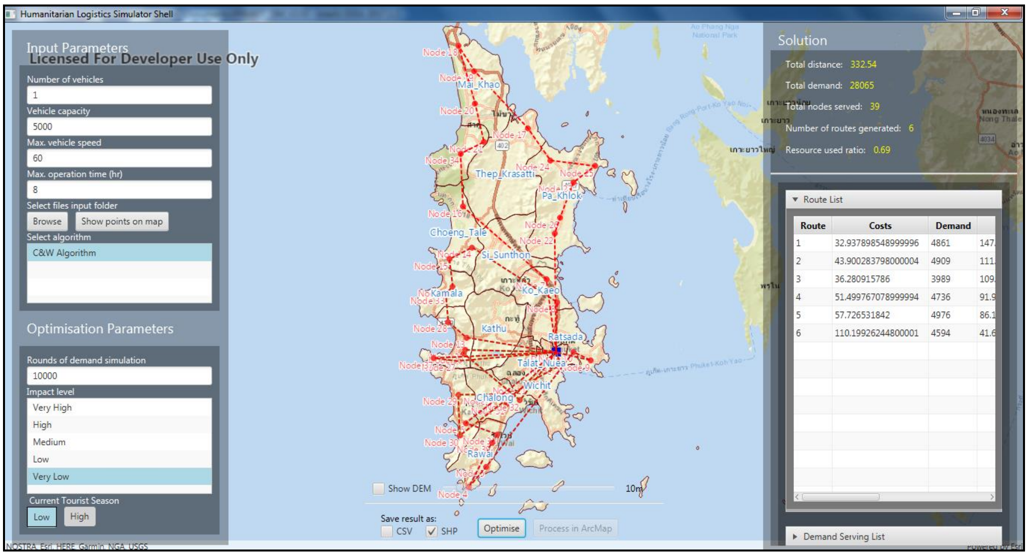


Figure 7-9: Presentation of the scenario solution using parameter $t_l : r_1$.

The solutions displayed on the HLO user interface for the proposed scenario include routing visualisation and numerical results, consisting of total distance used, total demand served, total node served, number of routes generated and resources used ratio (see Table 7.7).

Solution	Outcome	Unit
Total distance	332.54	Km
Total demand	28,065	Bag
Total nodes served	39	Site
Number of routes generated	6	Route
Resources used ratio	0.69	-

Table 7-7: The overall solution for the proposed scenario.

Regarding the optimization solution, the overall visualisation map for the generated routes is immediately shown on the user interface. The user is also given a list of routes ordered by priority and details such as nodes visited in the route and total demand served in the route.

The routing solutions are illustrated in accordance with the routing priority as illustrated in Table 7.8. Each route includes its cost, total demand served by the vehicle, demand-cost efficiency and evacuation nodes visited by the vehicle which starts and ends at node 1, which is the depot (DDPM Regional Office no. 18, Phuket).

Route	Cost (km)	Total demand served	Demand-cost efficiency	Nodes visited
1	32.93	4,861	147.58	1 - 32 - 36 - 35 - 1
2	43.90	4,909	111.82	1 - 2 - 11 - 30 - 29 - 3 - 31 - 1
3	36.28	3,989	109.95	1 - 27 - 37 - 1
4	51.50	4,736	91.96	1 - 8 - 14 - 15 - 12 - 33 - 28 - 13 - 1
5	57.73	4,976	86.20	1 - 6 - 38 - 39 - 4 - 5 - 10 - 9 - 1
6	110.20	4,594	41.69	1 - 7 - 16 - 34 - 21 - 20 - 18 - 19 - 17 - 24 - 25 - 23 - 26 - 22 - 1

Table 7-8: Routing solutions for the proposed scenario.

The following figures illustrate each routing map according to numerical solutions given in Table 7-8. The tables accompanying the figures present the quantity of demand served in each evacuation node which can be viewed on the user interface.

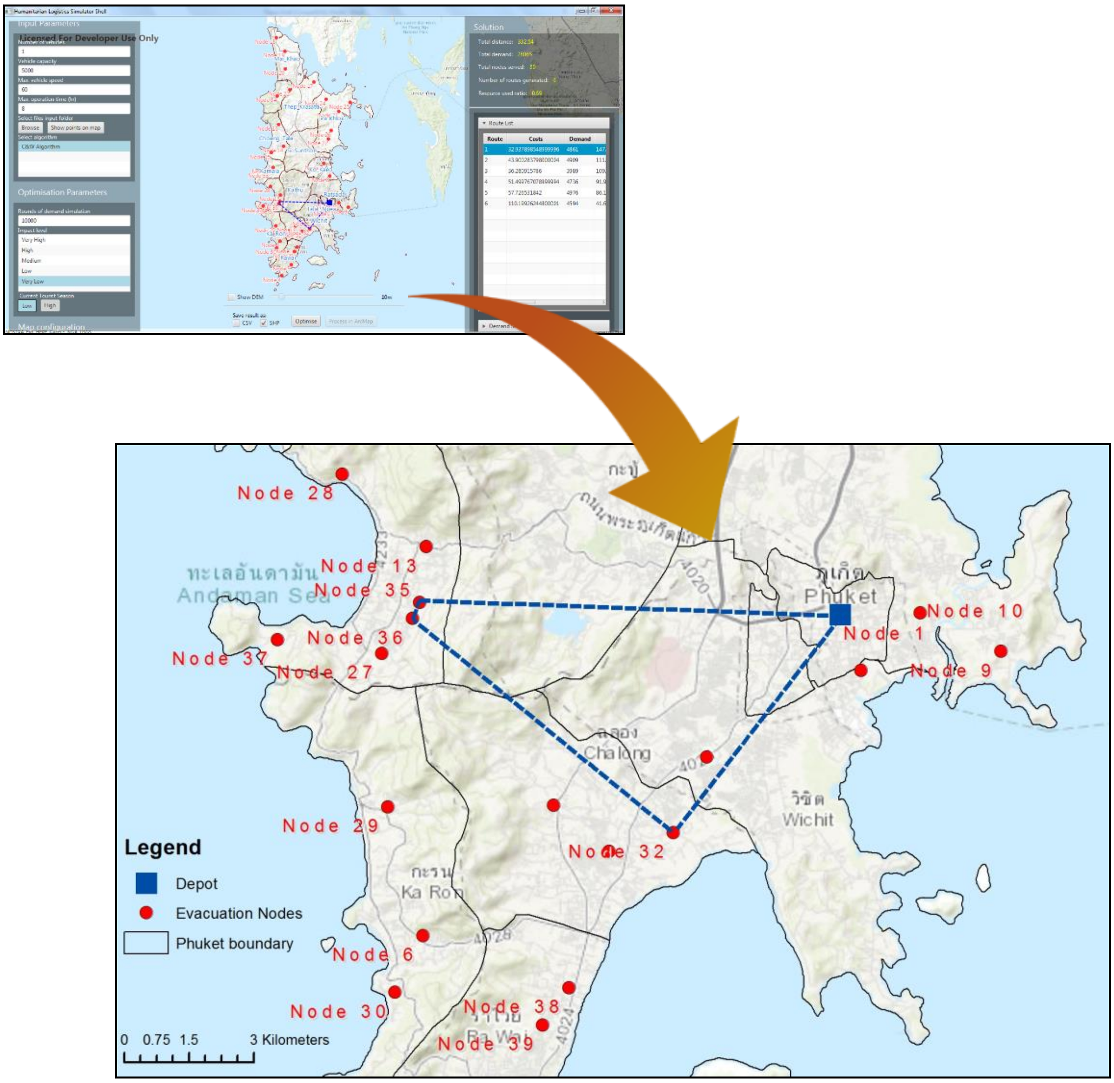


Figure 7-10: The visualization of route 1 displayed on the DSS user interface.

Sequence	Node ID	Demand served
1	32	1,077
2	36	2,131
3	35	1,653
	Total demand	4,861

Table 7-9: Demand served in each evacuation node in route 1.

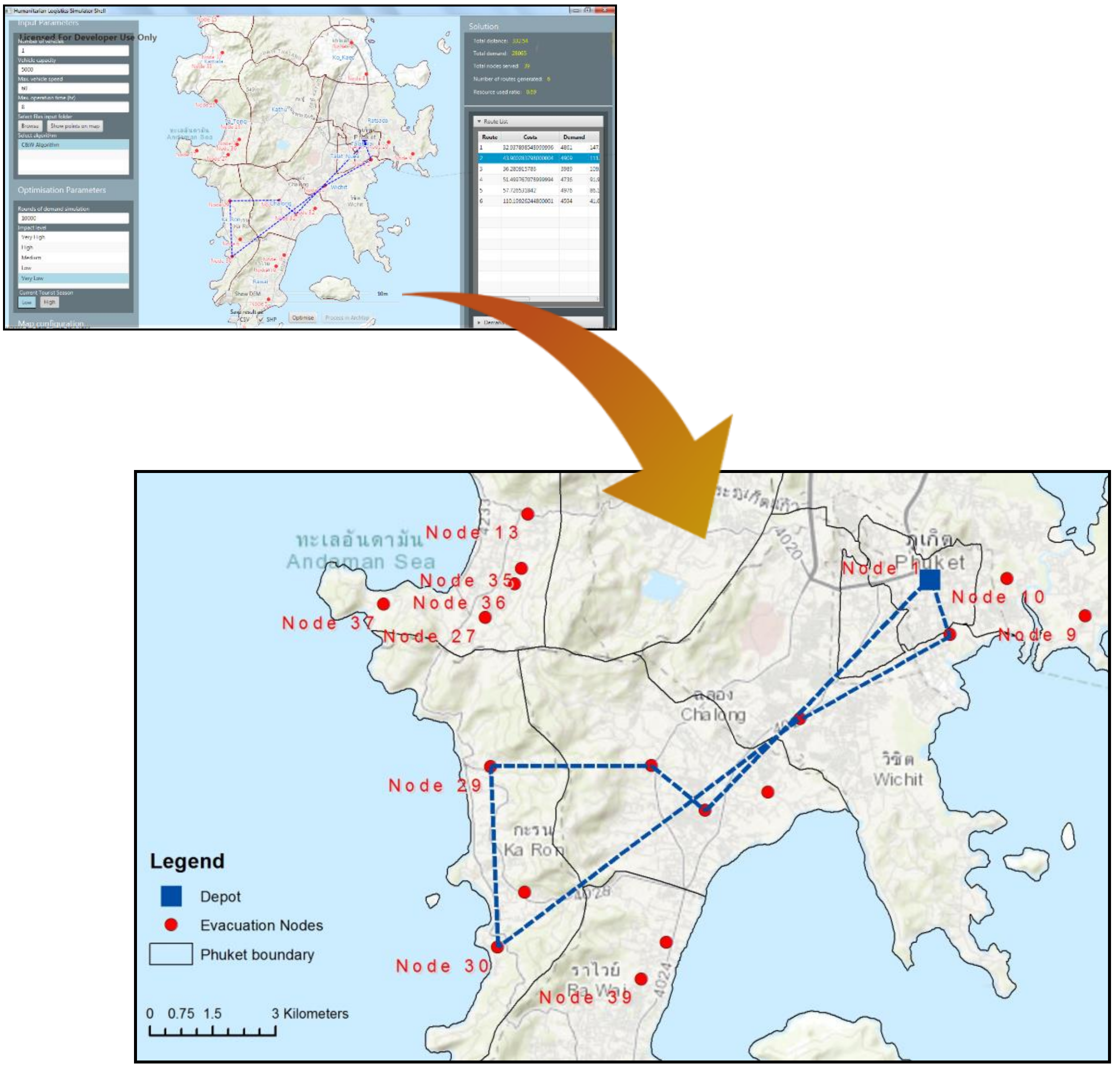


Figure 7-11: The visualization of route 2 displayed on the DSS user interface.

Sequence	Node ID	Demand served
1	2	45
2	11	105
3	30	929
4	29	2,310
5	3	394
6	31	1,126
	Total demand	4,909

Table 7-10: Demand served in each evacuation node in route 2.

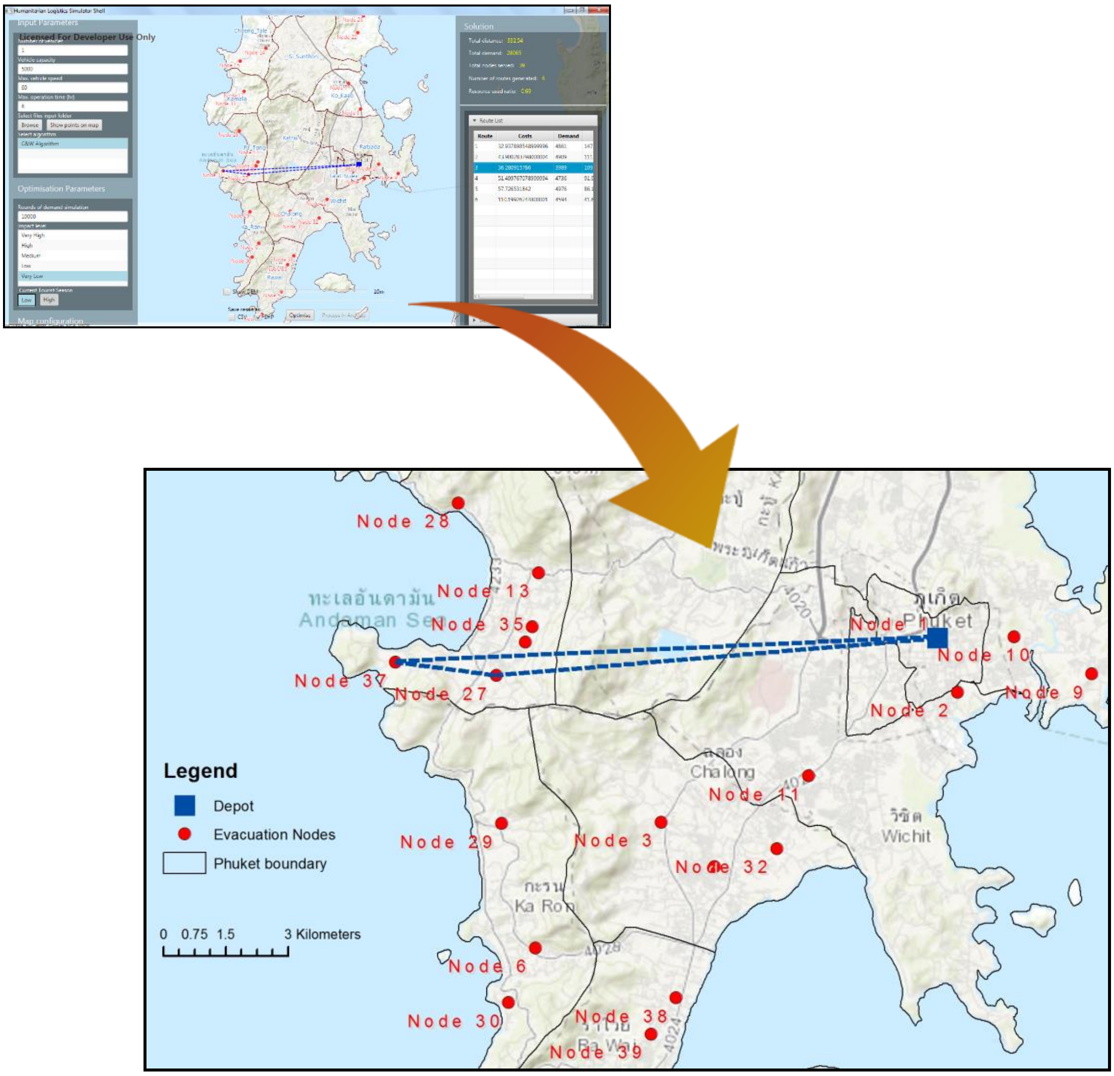


Figure 7-12: The visualization of route 3 displayed on the DSS user interface.

Sequence	Node ID	Demand served
1	27	3,394
2	37	595
	Total demand	3,,989

Table 7-11: Demand served in each evacuation node in route 3.

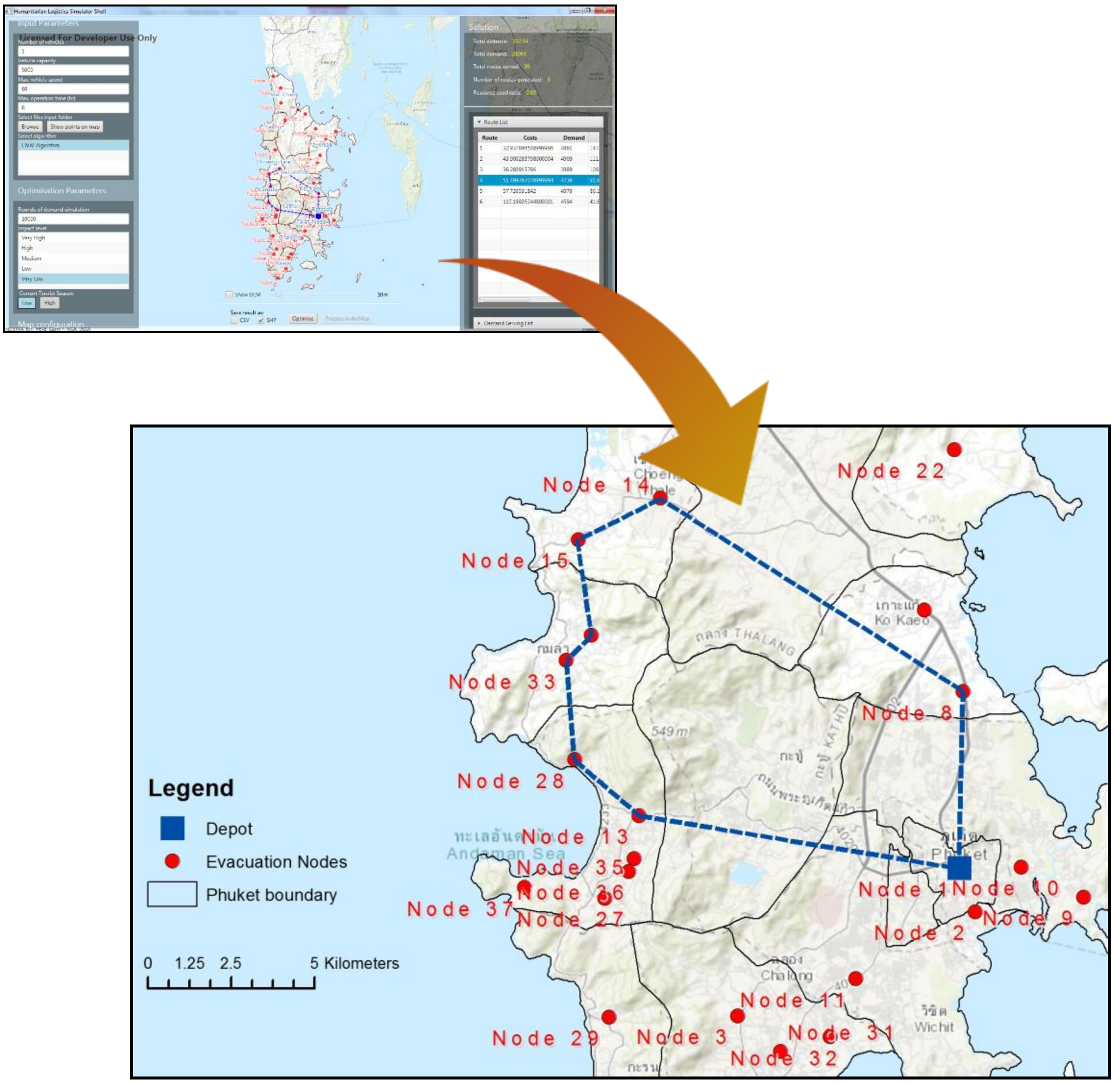


Figure 7-13: The visualization of route 4 displayed on the DSS user interface.

Sequence	Node ID	Demand served
1	8	116
2	14	794
3	15	1,674
4	12	1,152
5	33	826
6	28	96
7	13	78
	Total demand	4,736

Table 7-12: Demand served in each evacuation node in route 4.

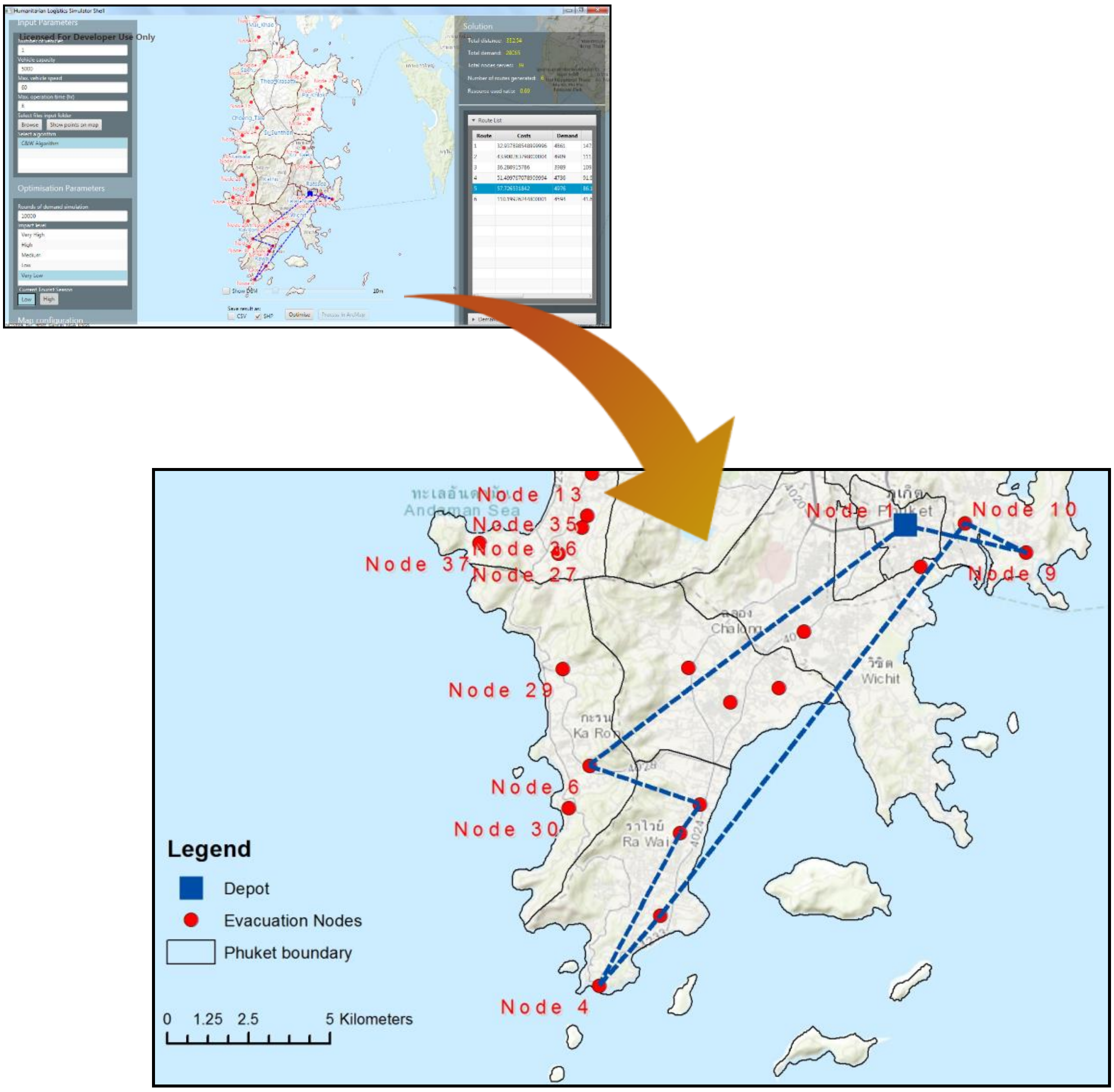


Figure 7-14: The visualization of route 5 displayed on the DSS user interface.

Sequence	Node ID	Demand served
1	6	1,813
2	38	57
3	39	53
4	4	1,862
5	5	499
6	10	574
7	9	118
	Total demand	4,976

Table 7-13: Demand served in each evacuation node in route 5.

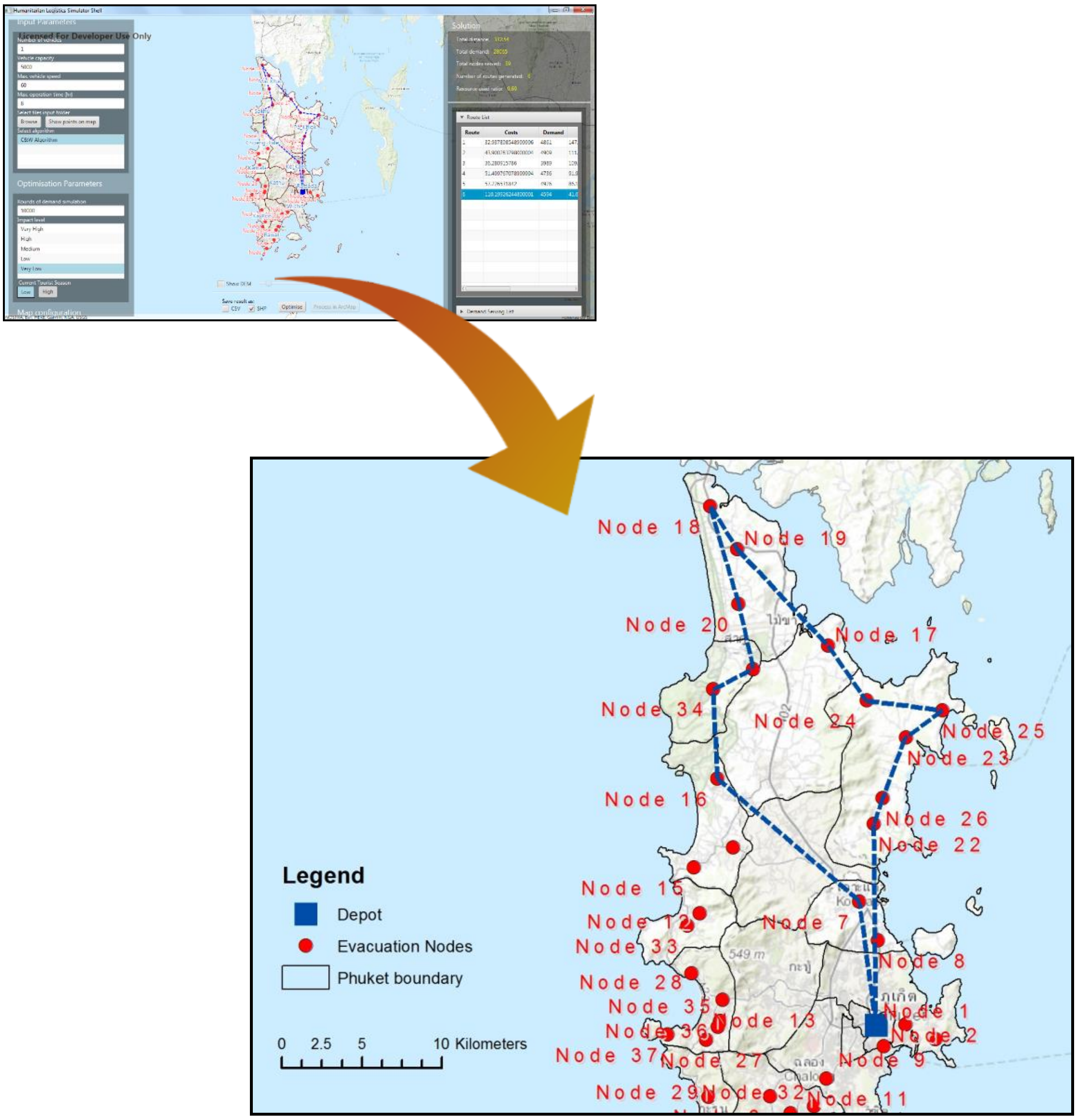


Figure 7-15: The visualization of route 6 displayed on the DSS user interface.

Sequence	Node ID	Demand served	Sequence	Node ID	Demand served
1	7	13	8	17	363
2	16	309	9	24	70
3	34	404	10	25	1,230
4	21	655	11	23	35
5	20	638	12	26	48
6	18	669	13	22	16
7	19	146		**Total demand**	4,594

Table 7-14: Demand served in each evacuation node in route 6.

Furthermore, each routing solution is automatically converted into a GIS shapefile that can be imported to the ArcGIS platform and used to generate a visualisation map as shown Figures 7-16 to 7-21. The ArcGIS Network Analyst feature enables the user to adjust the routes interactively to avoid roads damaged by the tsunami flood.

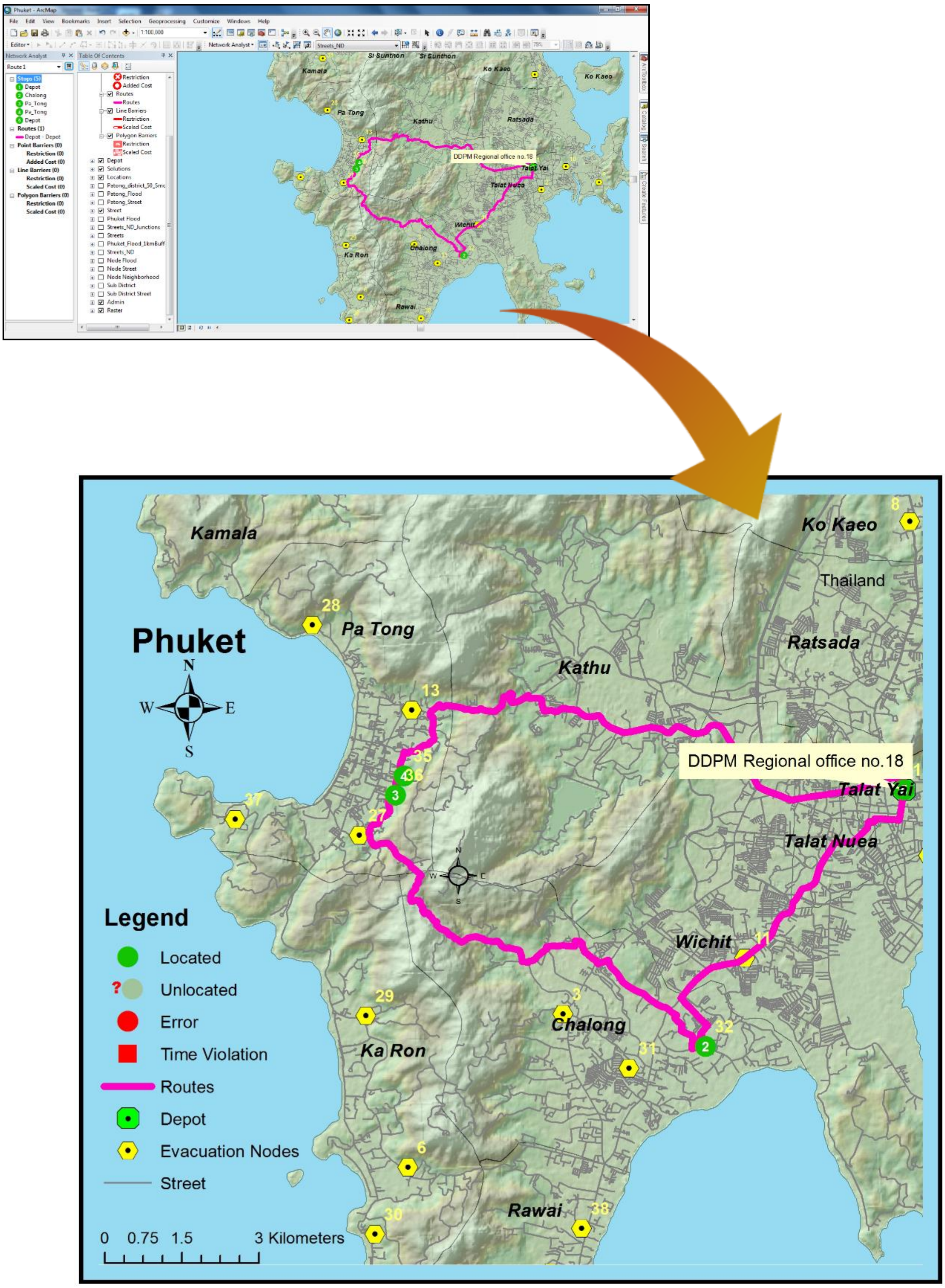


Figure 7-16: Visualization map of route 1 using ArcGIS Network Analyst.

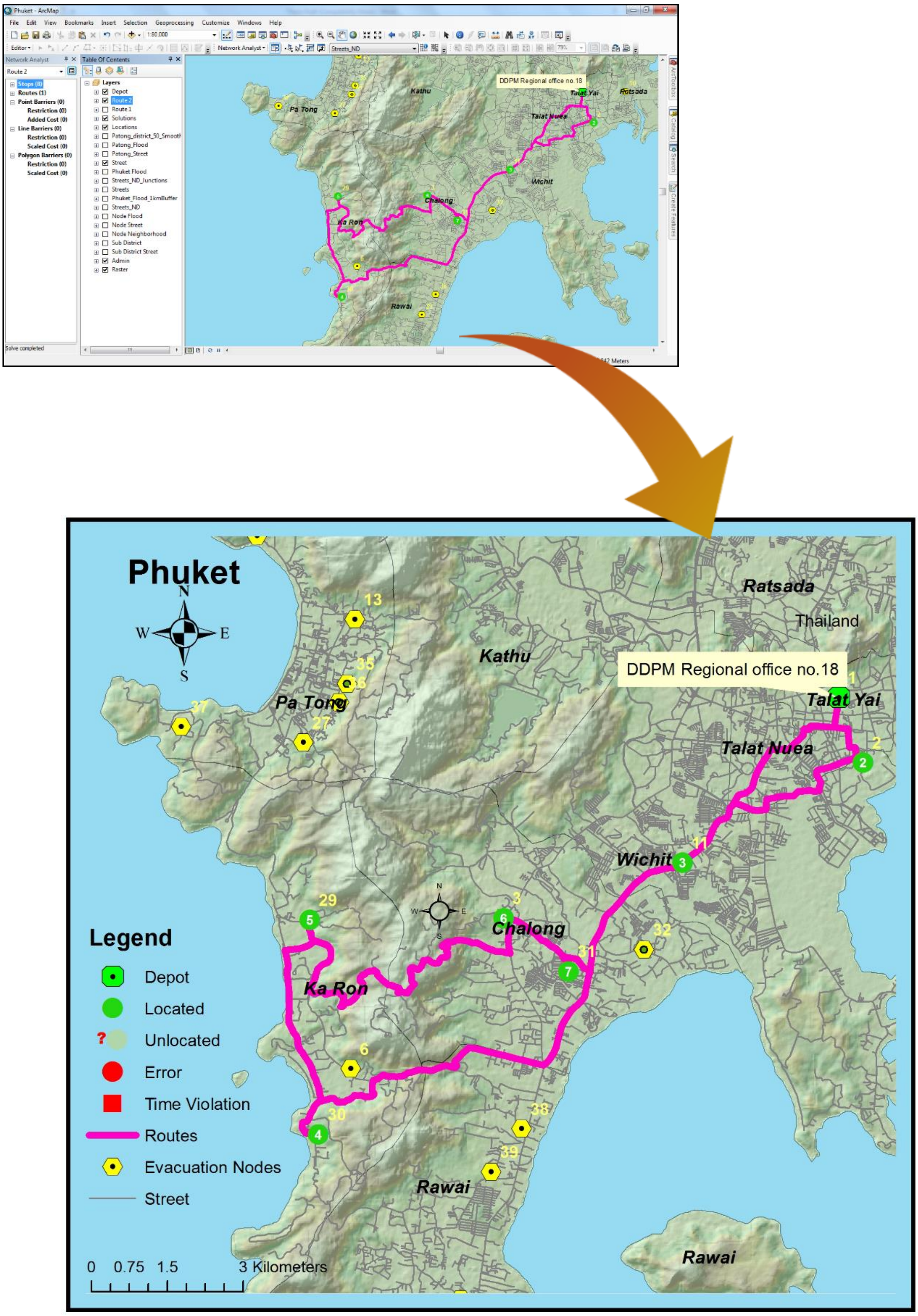


Figure 7-17: Visualization map of route 2 using ArcGIS Network Analyst.

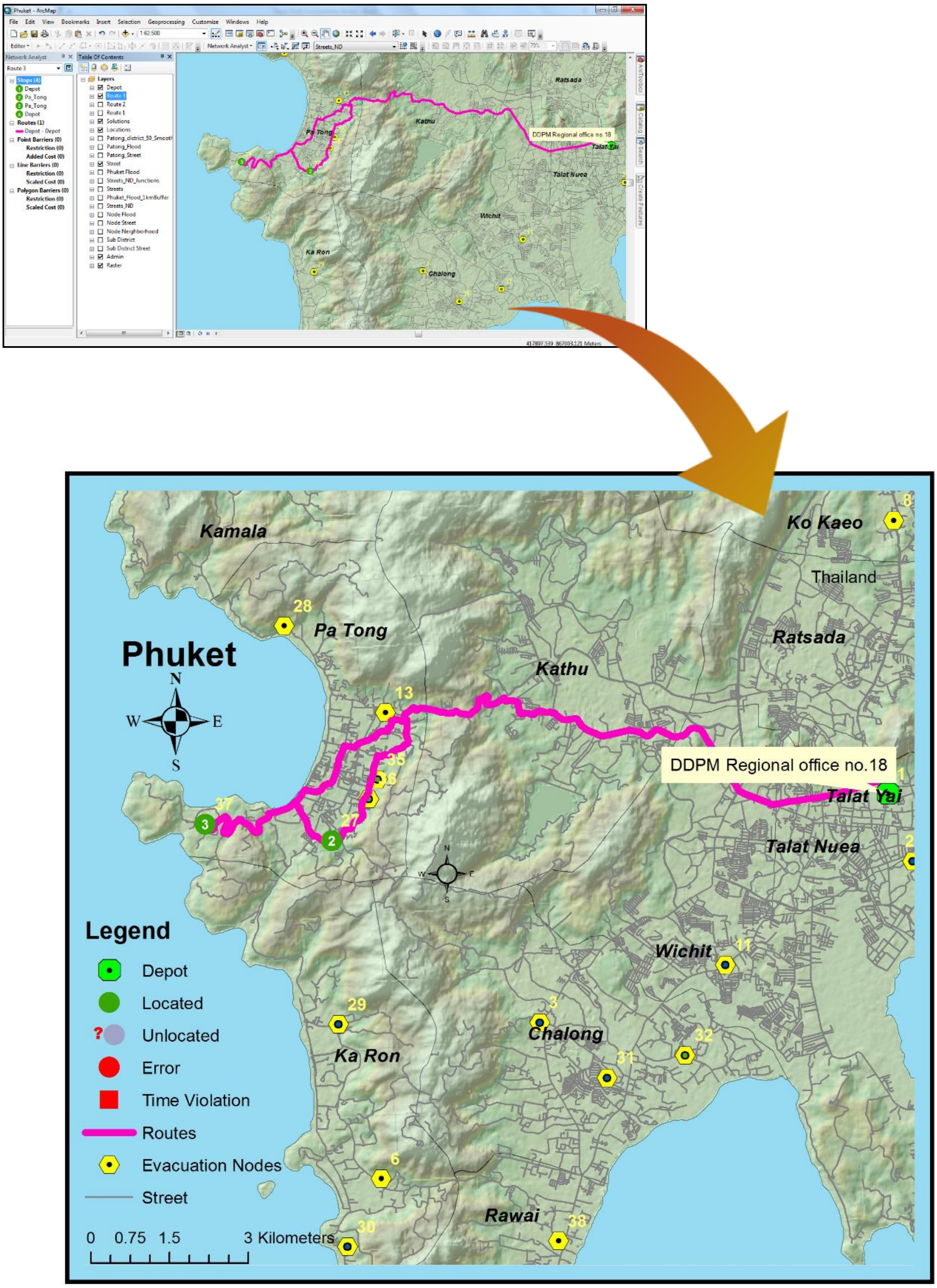


Figure 7-18: Visualization map of route 3 using ArcGIS Network Analyst.

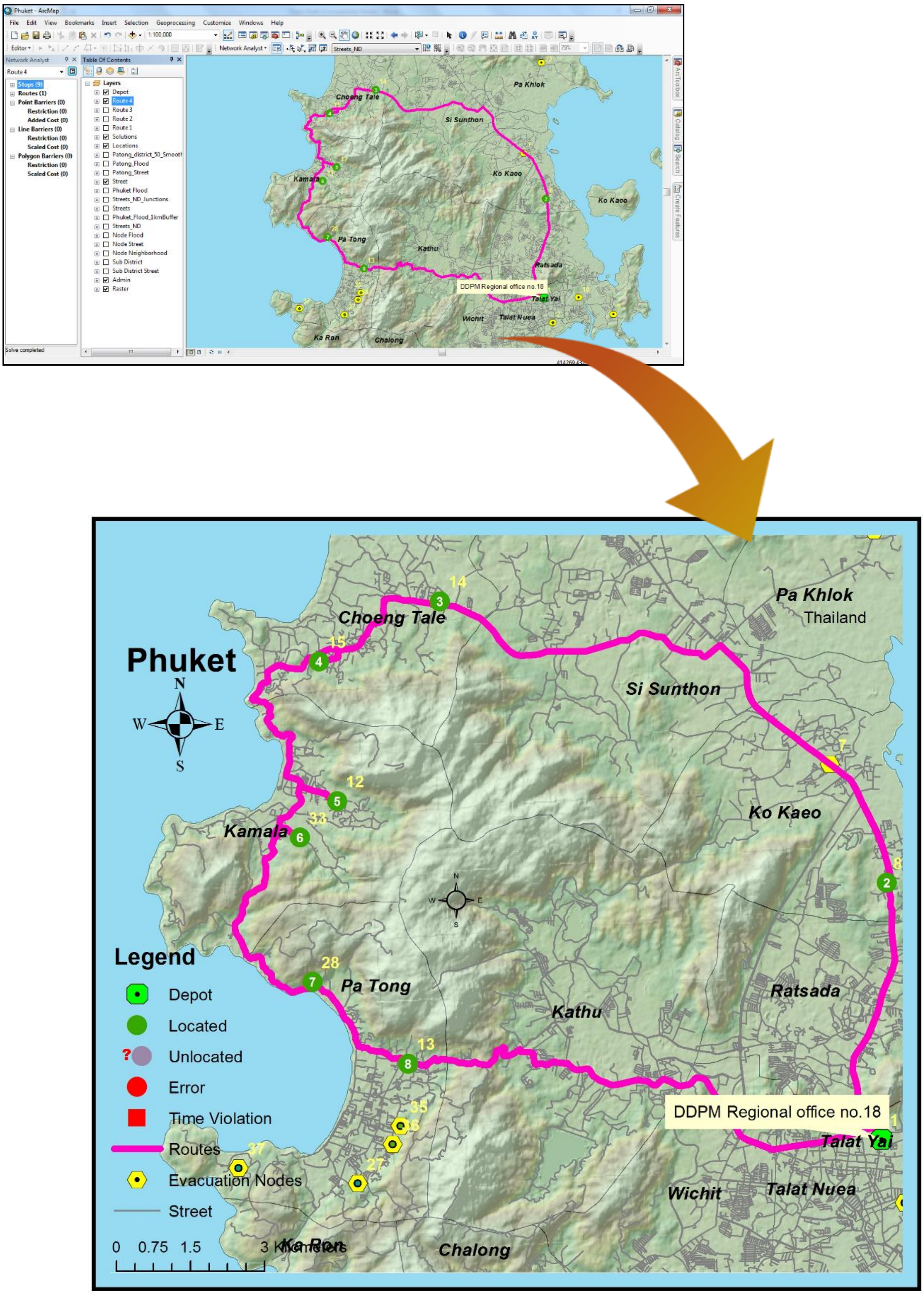


Figure 7-19: Visualization map of route 4 using ArcGIS Network Analyst.

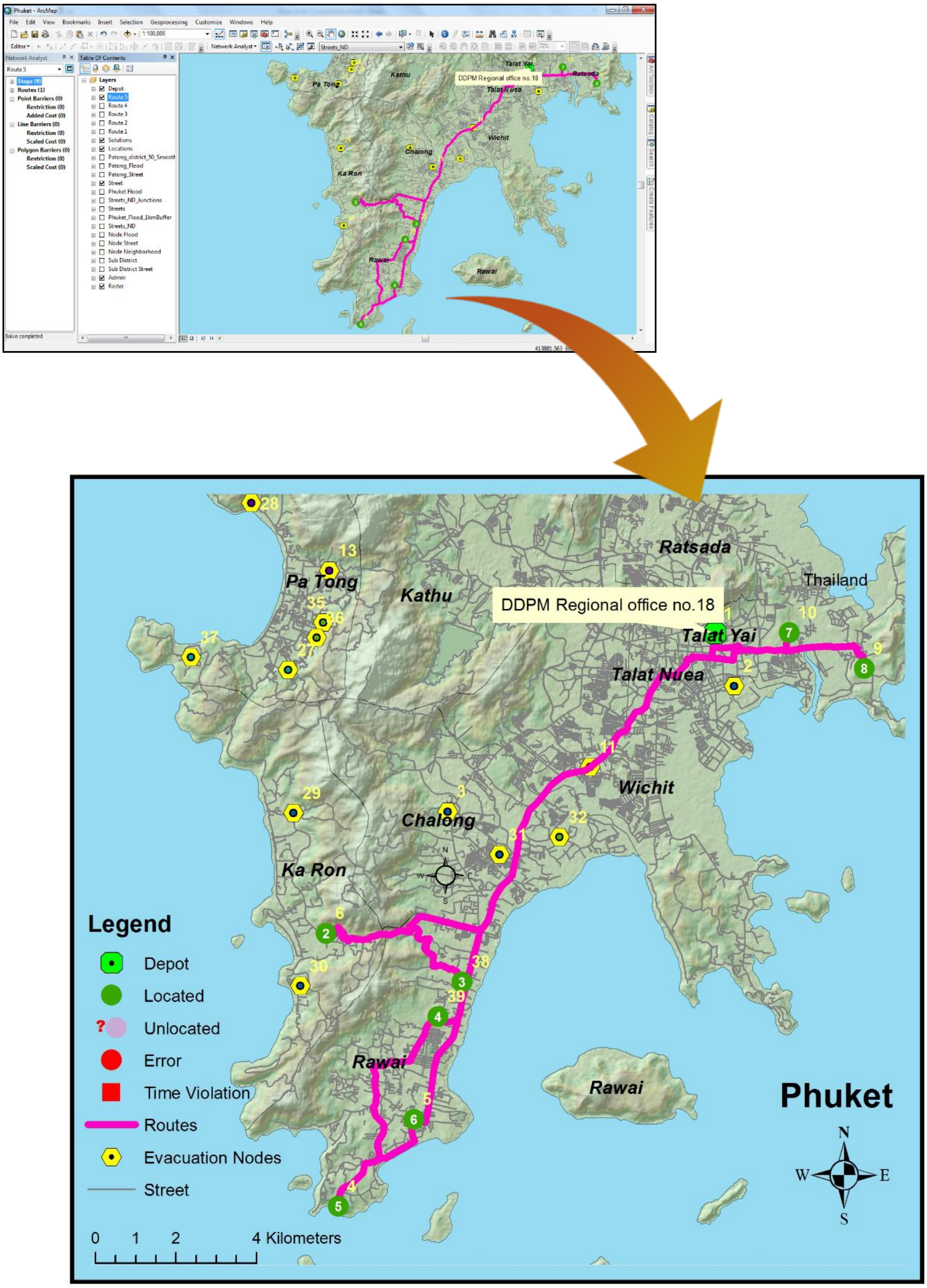


Figure 7-20: Visualization map of route 5 using ArcGIS Network Analyst.

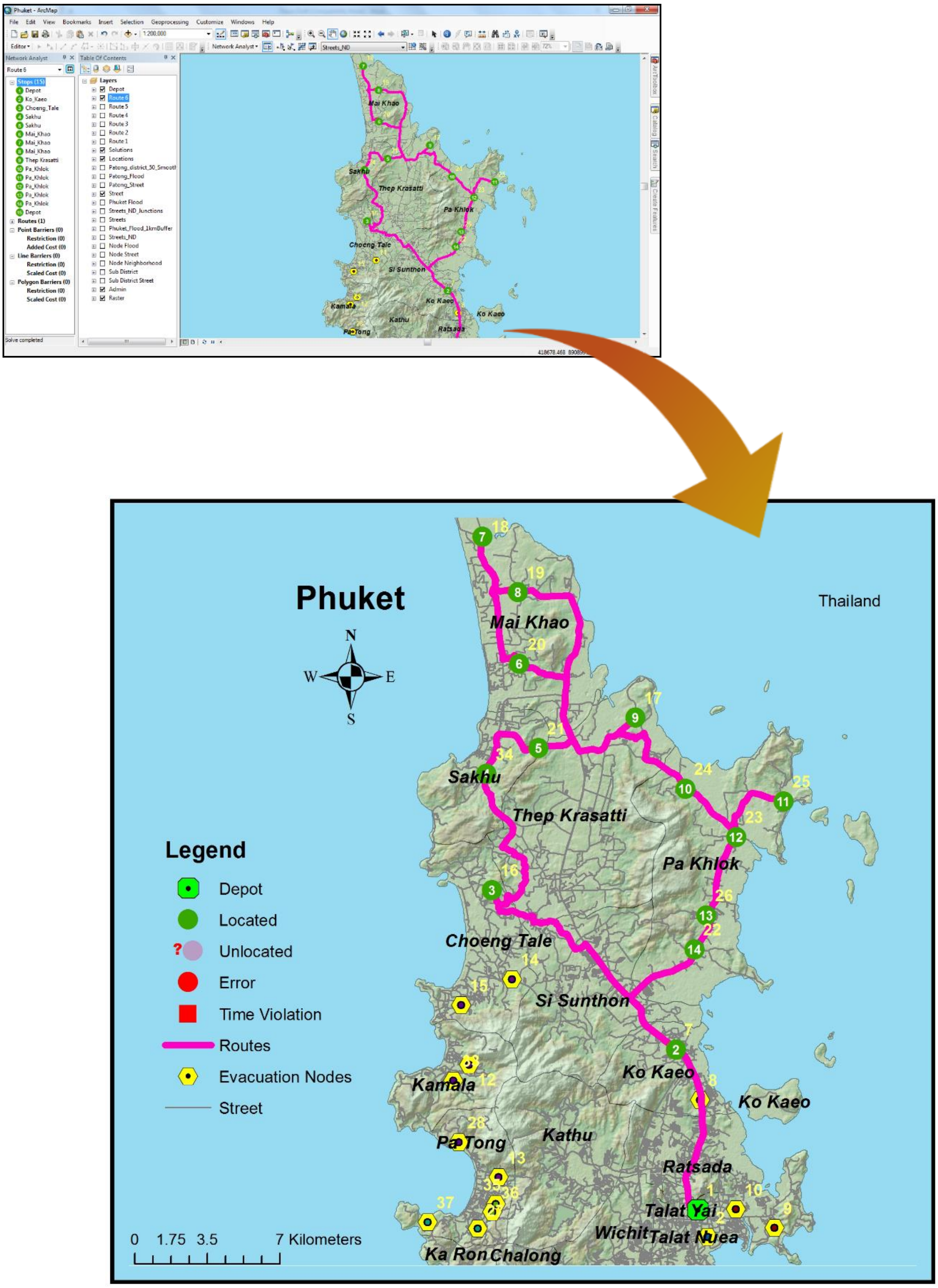


Figure 7-21: Visualization map of route 6 using ArcGIS Network Analyst.

7.7 Chapter Summary

This chapter presents a DSS by combining GIS and CVRP optimization for humanitarian logistics using the case study of a tsunami in Phuket, Thailand. The structure of the proposed DSS consists of two main components – APE and HLO modules – which were developed based on the ArcGIS system. The key purpose of the GIS-based DSS is to facilitate the decision-making regarding logistics planning and operation and the management of transportation resources.

The main function of APE is to estimate the number of people affected by a tsunami based on a set of user-provided parameters. As a result, the solutions are produced and assigned to each evaluation site, which are pre-defined as the safe places across the study area. The number of people estimated for each evacuation node is, in turn, referred to as the quantity of demands to be delivered for those affected. The solutions generated from the APE application are linked to the HLO module and then used as important input data in the HLO system.

In the HLO environment, the user must estimate a set of variables of transport resources to be used for the logistics operation. Moreover, other input data, e.g. seasonal parameters including the tourist season and the time of a day, play a vital role in generating the CVRP solutions. The given parameters will affect the demand simulation which uses the Monte Carlo technique to produce a range of possible outcomes. By simulating the demand assigned to a set of evacuation nodes, the CWS algorithm is then applied to obtain the routing optimization solutions. In addition to numerical results, the DSS produces an instant map of the solutions that enables the user to visualise the planned routes.

Furthermore, the HLO automatically generates the routing solutions in the form of GIS shapefiles that can be linked to the ArcGIS platform. In the ArcGIS system, the user can manipulate the solutions by using the Network Analyst functionality. In this way, the user can operate interactively the geographic solutions to solve any problems that may occur during the response phase. Therefore, the GIS-based DSS is very useful for facilitating decision making in both the preparedness and response stages of a tsunami disaster.

Chapter 8: Conclusion

8.1 Conclusions and Recommendations

The impact of the vast tsunami attack on Phuket coastal communities in 2004, ranging from the sudden-onset occurrence of the catastrophe to its potentially devastating consequences, required disaster stakeholders and related communities to better prepare for a future event by constructing a tsunami warning infrastructure and developing evacuation plans. On a local scale, however, there is still a lack of decision support mechanisms for delivering basic needs to the affected population in an efficient manner. To fill this gap, this research adds to ongoing study efforts that seek an advantage by integrating Geographic Information System (GIS) and Capacitated Vehicle Routing Problem (CVRP) optimisation for humanitarian logistics.

The research framework in this study consists of three main stages: population estimation, CVRP optimisation and development of a Decision Support System (DSS). In the first stage, this research proposes a means to estimate, in various tsunami scenarios, the number of people in each evacuation shelter, using areal interpolation techniques which are analytically processed in the GIS environment. Estimating the affected population relies on not only on tsunami severity but also on factors such as the buffer distance to those indirectly affected, the town elevation and the population of the towns under consideration.

After estimating the population affected by a tsunami in each evacuation node, the numbers then are referred to demand quantities so that the second phase of this research presents the Clarke and Wright Saving (CWS) algorithm to solve the CVRP optimisation. By doing this, a set of relief routes are determined with the minimum cost. Also, the solutions include secondary information for making decisions about managing transportation resources and prioritising routes in case of a transportation resources shortage.

The first two study stages are combined to develop a GIS-based DSS for humanitarian logistics. This decision support technology consists of two linked subsystems, the Affected Population Estimation (APE) and Humanitarian Logistics Optimization (HLO) modules. APE is an application developed for estimating the population affected by a tsunami inundation. The results generated by APE can be linked and used in the HLO environment. The main function of the HLO system is to produce a logistics plan in accordance with the data and parameter input.

The solutions serve the decision maker in two aspects: numerical and geographical formats. The numerical results, accompanied by the visualization maps, enable the decision maker to manage the logistics plan more efficiently and effectively. Moreover, the plan can be interactively operated in real-time deliveries as the routing solutions are generated in the form of GIS shapefiles. If a planned road network cannot be used for deliveries due to tsunami destruction, this feature enables the decision maker to reroute to avoid such a damaged road network based on the least cost in the ArcGIS environment by using Network Analyst capability.

In practice, the proposed DSS can be used in the preparedness phase for simulating the demands and subsequent delivery route planning to determine the transportation resources needed. If a tsunami occurs, the system also enables the decision maker to determine a set of map routes in real-time in cases of either known or unknown demands. In such a situation, the system also enables the user to quickly adjust road maps if part of the solution is restricted due to the tsunami impact.

To implement the proposed DSS for a stakeholder in the DDPM, the local relief distribution in Phuket requires a DSS to contain a map visualisation feature to improve decision making in humanitarian logistics. Moreover, the DDPM director also needs mechanisms that make the distribution operate efficiently and effectively. Because of this research, the GIS-based DSS developed for visualising and optimising distribution plans for humanitarian logistics would meet the requirements of the DDPM Reginal Office No. 18.

With respect to utilising the proposed DSS, the DDPM office needs a computer system that meets specifications to ensure it can run GIS applications such as ArcGIS software, which is a requirement for implementing the GIS-based DSS. Moreover, quality input data must be provided regularly to obtain reliable solutions.

Furthermore, this GIS-based system can be implemented in other tsunami hazard areas for which the DDPM or other stakeholder organizations in Thailand are responsible, if the detailed geodatabase of every area is available. In the future, this same type of technology can be implemented in other modes of transportation for humanitarian logistics.

In addition, the system proposed in this research could be used for managing humanitarian logistics in flood disasters that have frequently occured in other parts of Thailand. This is particularly the case in the central and the north-east of the country where the population are vulnerable to flood inundation in the rainy season which is largely dominated by the monsoon. Hence, the DDPM regional offices in those areas are able to use the GIS-based DSS to plan for and respond to relief logistics in a case of flooding situations. Moreover, not only in Thailand, this developed DSS can be used in other coastal countries where flooding is considered as an important threat to their population.

Last but not least, in order to maximize the performance of the DSS proposed in this research, the stakeholders related to disaster prevention and mitigation are suggested to retain evacuation structures such as signposts and evacuation route maps in good and updated condition. Likewise, local communities have to be educated and trained on a regular basis concerning the existing tsunami evacuation plan to ensure that, when a tsunami warning is triggered, they can move to the right place at the right time.

8.2 Research Contributions

This dissertation is expected to contribute specifically to humanitarian logistics research and broadly to applications related to decision making. It is hoped that this research will widen the understanding of estimating affected populations and highlight the role of population-relevant variables in the estimation process using GIS and subsequently implementing CVRP algorithms to simulate route maps to plan for and respond to disaster situations. The models and results presented should be treated as developing efforts to better link population estimation research and transportation modelling for humanitarian logistics. Finally, this research has provided the GIS-based DSS framework for facilitating decision-making regarding relief logistics in the aftermath of a tsunami event.

The contributions of this research are explained in accordance with the research objectives, outlined in Chapter 1. Thus, a summary of the contributions follow.

Objective 1: Design and develop a spatial algorithm to estimate the population affected by a tsunami inundation.

The first objective was achieved by reviewing the relevant existing literature regarding population estimation. The population data and estimation literature is a broad and well-established field. The ultimate focus of this literature review was to examine the methods used to measure the number of people affected by a disaster. Its specific purpose was to assess affected numbers in a tsunami flood model, which was undertaken within the case study chapter (Chapter 5).

The challenge found in the literature was that, in a disaster situation, using the whole population in an administrative area could distort the analysis as the disaster rarely respects geographical boundaries. The administrative population records of the area, however, could be used as an estimation basis. According to Wu *et al*. (2008) and Chen (2002), such data can be combined with population-relevant variables such as land use and street networks to generate a feasible image of how populations are spatially distributed in the area. This approach is called dasymetric-mapping spatial interpolation. A study by Reibel and Bufalino (2005) reveals that spatial interpolation using a street-weighted method improves performance in terms of error reduction. As a result, this research seized the dasymetric-mapping method using a road network as ancillary information to estimate the affected population in the study area.

Objective 2: Develop and implement an application by combining GIS and the population estimation method.

From the National Research Council's (2007) perspective, the quantitative expression of the size of the population affected by a disaster can be obtained using the hazard assessment process. In addition, a concept provided by Ranjbar *et al.* (2017), Doocy *et al.* (2007) and Balk *et al*. (2005) was a notable inspiration for modelling tsunami hazard areas using GIS. Therefore, before calculating the affected numbers, this research proposed GIS techniques to model the tsunami hazard area so that the population data was downscaled to the hazard area and then the spatial interpolation techniques were implemented to obtain the estimation solutions.

To fulfil this objective, an application was developed based on the proposed spatial interpolation techniques for estimating the population affected by a tsunami inundation. Python computer programming was used to design and create the application. The Python commands are automatically executed in the ArcGIS environment to build tsunami hazard models and subsequently calculate affected locals based on parameters given by the user. The solutions are distributed to each evacuation node in which its position (latitude and longitude) and a range of affected numbers are contained. In addition to instantly displaying the solutions on the user interface, the application was designed to create the solutions in the form of a spreadsheet file so that it can be used as input data for the CVRP optimisation.

Objective 3: Implement a CVRP model and its solution method for aid delivery in the aftermath of a tsunami.

This objective was accomplished by reviewing the relevant literature regarding CVRP and its solving methods. The CVRP mathematical model in this research was fundamentally inspired by Bodin *et al.* (1983). As this study dealt with routing problems in catastrophic events, the CVRP formulation was improved to capture the important aspect of real life transportation because Ak and Erera (2007) and Qin *et al.* (2017) notably propose that the classical CVRP is oversimplified and treated as a deterministic demand, especially in emergency situations. As a result, the proposed model was designed to cope with delivery under demand uncertainty by allowing a demand node to be revisited if its demand quantity is greater than the vehicle capacity.

In addition to the demand aspect, a suggestion by Balcik *et al*. (2008), Ichoua (2010) and Qin *et al.* (2017) noted that supply of emergency and transportation resources are limited in an emergency CVRP. Their perspective stimulated this research to take transportation resources into solutions so that the decision maker can manage the transportation assets to meet the operation goal.

With respect to solving methods, this research used the CWS heuristic, proposed by Clarke and Wright (1964), to solve the proposed CVRP model due to its simplicity of implementation and efficient calculation speed. This choice of method was supported by Juan *et al.* (2010), who claimed that the simplicity and flexibility of implementation of the CWS method is the most important aspect in real-world CVRP.

Objective 4: Develop and implement a DSS for post-tsunami aid delivery by integrating GIS and CVRP optimization for humanitarian logistics.

The purpose of this objective was significantly motivated by the limited research on development of a DSS for vehicle routing and applications for decision making in emergency sectors, especially implementing a GIS-based DSS for designing routes in tsunami inundations. As a result, the main objective was to develop a DSS by integrating GIS and a CVRP algorithm to facilitate decision making in humanitarian logistics operations in the aftermath of a tsunami.

This objective was achieved by using Java programming language to develop the GIS-based DSS on the IntelliJ IDEA development software. The system consists of two modules, one for estimating the affected population and the other for generating optimal routes in the form of visualization maps. The important feature of the proposed DSS is the inclusion of time-specific population estimates in the demand simulation process. The key function of the DSS is to produce the relief logistics model in the planning stage. In addition, the routing solutions are linked and can be analysed in real time by using Network Analyst in the ArcGIS platform. As a result, this key contribution would assist the decision maker to visually manage the humanitarian logistics in both disaster preparedness and response phases.

8.3 Research Limitations

This study is limited to the local area of Phuket, Thailand in which the Asian tsunami severely affected the population and infrastructure in 2004. Therefore, only supply centre and demand locations in this region were tested to find the solutions.

With regard to solution method, this research utilises the Clarke and Wright saving algorithm, because the simplicity of its implementation is considered to be more important than the solution quality. As a result, the routing solutions in this study are limited to near-optimum.

In addition to routing solutions, transportation efficiency and demand-cost efficiency (route priority) are developed and included in the solutions in order to facilitate decision making regarding transport resource management.

However, transport time in each route developed in the solutions does not consider service time (e.g. load and unload time) at all demand nodes.

Furthermore, the proposed DSS exploits Network Analyst in ArcGIS, which is a proprietary GIS software. Thus, the DSS user has to have this software installed in order that the DSS can be operated properly. By acquiring ArcGIS, the user may have to pay for a software license, which is relatively more expensive than those free and open source softwares.

Lastly, the DSS developed in this research is limited for a stand-alone computer. The solutions are not able to be shared to the relevant organizations in real time.

8.4 Suggestions for Future Research

Although this research focused on using data specific to Phuket, Thailand, the framework with all the tools and methods developed can be used in other geographical locations at risk of tsunamis or more general flooding. Future research might test the method presented in this dissertation at varying geographical scales, such as country level.

The most important elements of this research, in terms of its contributions to the field of relief logistics management, are the methods and the data that are used to estimate the affected population and to solve the CVRP model. The data used in this research to estimate the number of people affected by a tsunami flood were at the sub-district level. Applying the same methodology on a finer scale, data such as village scale may produce different results in terms of population estimation, which in turn would be reflected in more accurate routing solutions.

Furthermore, this research considered that the decision maker could prioritize the transportation resources to be used in the delivery routes generated in the solutions. The data used to produce the transportation resource measure were the number of vehicles, average vehicle speed and operation time. The data also assumed that a vehicle travels at an average speed through the designed routes without service time consideration. Future research may introduce service times into the problem so that identifying the usage of transportation resources would be more applicable.

This research employs Network Analyst in ArcGIS rather than a free and open source software (e.g. QGIS). This is due to the fact that, at this time, the ArcGIS Network Analyst can provide better network-based spatial analysis than QGIS. However, QGIS may be more developed in terms of network-based analysis in the future. Therefore, future research is recommended to use free and open source software like QGIS if its capabilities can meet the research requirements.

Finally, further research is recommended in the issue of online services. As data standards and information-sharing mechanisms evolve, it may become increasingly possible to create a GIS-based DSS web application for discussing situations and sharing information among stakeholders in an emergency response. This would facilitate the association of humanitarian coordinators performing distribution analyses relevant to each situation, improving logistics operations.

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Appendix A

Foundation of Natural Disaster

Natural Disasters

In recent years, several regions around the world have fallen victims to natural disasters on a massive scale. In 2004, an earthquake in the Indian Ocean triggered a series of tsunamis that caused damage and loss of lives to several coastal countries. In 2005, Hurricane Katrina and subsequent floods affected a large region in the United States, accounting for a great deal of residential damage; it ranked as the costliest natural disaster in the country's history. In addition to these catastrophes, past decades have seen many other large disasters, including the Nargis Cyclone; the Sichuan earthquake in 2008; the Haiti earthquake in 2010; and the Japan tsunami in 2011. The destruction from such natural disasters can leave populations without food and water, and essential medical care. This has brought attention to the need for methodology and technology to efficiently and effectively manage relief operations. Thus, the following section provides a description and a review of scientific knowledge of natural disasters in order to have a comprehensive recognition for developing potential methods for disaster relief.

Defining disaster

The term 'disaster' can be literally understood. However, it is actually not simple to define the term precisely (Norris *et al.*, 2006). The term can be distinctive when it is mentioned in different contexts. Thus, its definition must be clarified so it is relevant in the context of disaster relief. As seen in the literature, the term disaster has been defined by a number of sources as follows:

- *A potentially traumatic event that is collectively experienced, has an acute onset, and is time-delimited* (Norris *et al.*, 2006).

- *A disruption that physically affects a system as a whole and threatens its priorities and goals* (Van Wassenhove, 2006).

- *A serious disruption of the functioning of society, posing a significant, widespread threat to human life, health, property or the environment, whether caused by accident, nature or human activity, and whether developing suddenly or as a result of complex, long-term processes* (UN/ISDR, 2004).

- *A sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources* (IFRC, n. d.).

Humanitarian supply chains refer to a network of organizations and operations that attempt to alleviate the suffering of people caused by a disaster. Therefore, the term disaster must be related to what causes a calamity to people and communities that cannot be dealt with by using their prevailing resources. In addition, most disasters progressively affect the area in terms of the economy and the environment. Thus, the term disaster, as defined by the International Federation of the Red Cross and Red Crescent Societies (IFRC), is possibly suitable to be adopted in this research. The IFRC's term covers all the aspects that humanitarians have to take into account, especially for providing essential resources to alleviate the affected communities. Figure 1 illustrates an equation of disaster extent that usually depends on its impacts on affected areas and vulnerable people with the current resources to prevent and mitigate the disaster.

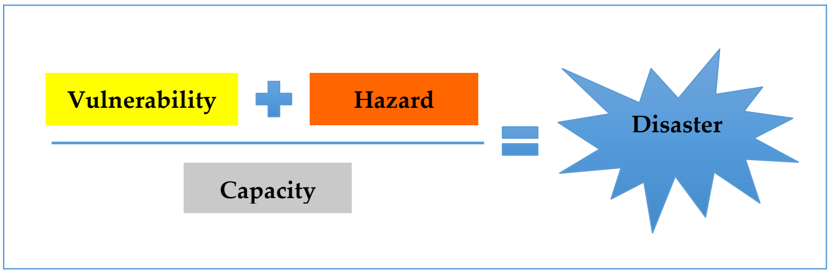


Figure 1: Disaster concept.

Source: International Federation of the Red Cross and Red Crescent Societies (IFRC)

It is worth noting that merely the concept of the term is inadequate to cover a successful humanitarian operation. Hence, more understanding of the disaster must be further reviewed in the following sections.

Disaster classification

Disasters normally are caused by either nature or humans, and are so-called natural disasters and man-made disasters, respectively (Cozzolino, 2012; Van Wassenhove, 2006). In addition to the cause, a disaster can also be categorised by speed of onset. Van Wassenhove (2006) suggests that either natural or man-made disasters can be classified into two types of occurrence: sudden-onset and slow-onset. Some examples of disaster with respect to the cause and speed of occurrence are shown in Figure 2.

	Natural	Man-made
Sudden-onset	Earthquake Hurricane Tornado	Terrorist Attack Coup d'etat Chemical Leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

Figure 2: Disasters with respect to cause and speed.

Source: Van Wassenhove, 2006

Interestingly, Cozzolino (2012) has combined Van Wassenhove's timely disaster occurrence with the determinant of logistics contribution. This leads to more understanding of the relationship between required logistics effort and disaster attributes, which is illustrated in Figure 3. As a result, sudden-onset disasters need more logistics effort; on the other hand, a lower level of logistics effort is needed for slow-onset disasters.

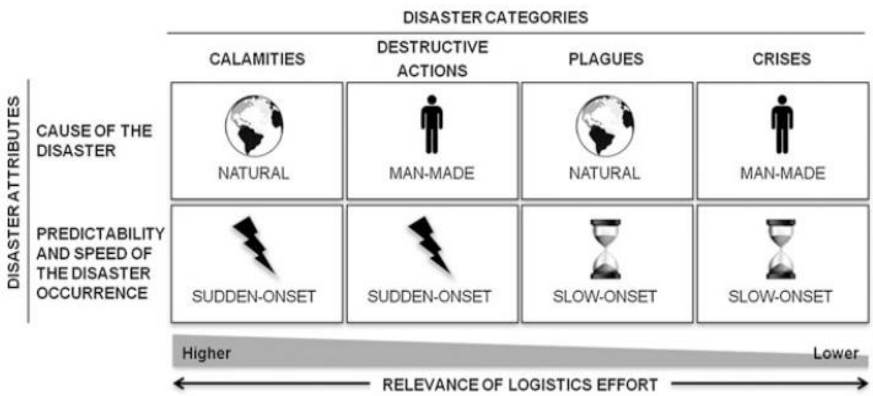


Figure 3: The relationship between disaster attributes and logistics effort.

Source: Cozzolino, 2012

More specifically, Figure 3 shows four different classifications of disasters, each of which is based on its cause and speed of occurrence. For instance, a calamity is considered as a natural disaster with a sudden-onset appearance, such as an earthquake or hurricane. With regards to a sudden-onset disaster, it comes very quickly to an area and can leave much destruction and many casualties behind. For example, a tsunami is a sudden-onset natural disaster having little warning, yet capable of generating impacts on local to regional geographical boundaries (Peduzzi, 2004, cited in Freire *et al*., 2013), and destroying everything in its path. This may result in a difficulty in accessing the crisis area, as well as relieving the affected people. Thus, a development of mechanisms to increase capability for disaster prevention and mitigation is required, particularly in earthquake and tsunami incidents.

As such disasters are striking more frequently and severely, disaster relief has become a more popular subject across the world. Humanitarian logistics, for example, has received a great deal of attention from both researchers and practitioners, especially after the occurrence of the Indian Ocean tsunami in 2004 (Kovács and Spens, 2007). Consequently, it is valuable to conduct a research that aims to develop an innovative tool for better managing disaster relief. In order to establish such a tool, the involvement of humanitarian aspects in each disaster phase must be examined. Thus, the next section provides a description of disaster management, followed by an investigation of the relationship between relief mechanism and disaster phase.

Disaster management cycle

Most disasters are characterised as emergency events and generally unpredictable. Thus, humanitarian logistics is one of the most difficult operations for alleviating the suffering of people. This is consistent with Long (1997), who argues that disaster relief is a highly specialised form of logistics for non-routine tasks and cannot be forecast with any significant degree of specificity. Hence, it is not easy to manage aid deliveries in such an event due to its uncertainty and complexity. Thus, reviewing the disaster management cycle is necessary to obtain more understanding of disaster characteristics.

Disaster management is often explained as a multiphase process (Cozzolino, 2012; Dé Silva, 2001), which is normally composed of mitigation, preparation, response, and reconstruction, as shown in Figure 4.

Figure 4: Disaster management cycle.

Source: Gour, 2014

In each phase, mechanisms or activities are considered in order to deal with a disaster. Possible mechanisms or activities in each disaster phase are shown in the below Table.

Disaster phase	**Mechanism / Activity**
Mitigation	Introducing laws and mechanisms that reduce social vulnerability (Cozzolino, 2012; Goldberg and Palladini, 2010) • Avoiding social construction on the shoreline (Van Wassenhove, 2006)
Preparation	• Pre-positioning of warehouses containing food and medical supplies (Van Wassenhove, 2006) • Developing response capacity (Goldberg and Palladini, 2010) • Developing evacuation plans (De' Silva, 2001) • Developing collaborative platforms among aid agencies (Kaatrud *et al*., 2003) • Developing humanitarian logistics software (Tomasini and Van Wassenhove, 2004)
Response	• Deploying supply chains (Tomasini and Van Wassenhove, 2004) • Distributing supplies to any point of demand (Long and Wood, 1995) • Minimize human and economic loss (Goldberg and Palladini, 2010)
Reconstruction	Assuring return to economic development and infrastructure development (Kovács and Spens, 2007; Mike and Eric, 2010)

Table: Mechanisms and activities in each disaster phase.

According to the Table, preparation and response phases seem to be more involved in disaster relief, because they contain essential mechanisms and activities of evacuation and distribution. Within these phases, some potential approaches can be developed, such as spatial decision-support systems, simulation techniques, distribution problems and vehicle routing problems for emergency environments (Barbarosoğlu *et al*., 2002; Hwang, 1999; De' Silva, 2001; Özdamar *et al*., 2004).

Moreover, Kovács and Spens (2007) suggest that humanitarian logistics efforts can be distinguished into two timely stages: continuous aid work and disaster relief. Continuous aid work engages with activities that are not suddenly required in the disaster environment, such as avoiding deforestation and building raised-bank structures to block tsunami waves. Hence, continuous aid work can be categorised as an activity required in the mitigation and reconstruction phases.

Regarding disaster relief, it is reserved for sudden-onset disasters (e.g. earthquake and tsunami, storm and flooding) in which humanitarian logistics is immediately needed in this stage. Thus, it implies that the disaster relief stage covers two disaster phases: preparation and response.

Likewise, Long (1997) states that preparation and response phases correspond to strategic planning, which is prepared for emergency projects, and contingency planning, which is implemented when a disaster strikes. These phases, therefore, seem to contain activities that are important not only for prevention, but also for alleviation of suffering from a disaster, such as a tsunami, which is the case study in this research. Thus, it is necessary to have a further review of tsunami disasters.

Appendix B

Foundation of Tsunami Characteristics and Tsunami Hazard Aessessment

Tsunami Characteristics and Hazard Assessment

During the last 20 years, many coastal communities across the world have suffered extensive damage from coastal disasters, such as storm surge, seawater flooding and tsunami. Among these coastal disasters, tsunamis usually are probably the most unexpected and cause the greatest devastation to coastal communities in which efficient humanitarian response is needed for alleviating affected people in the aftermath of such an event. Thus, development of measures to deal with the complex response due to a severe consequence of the tsunami is urgently required for efficient and effective humanitarian logistics. To this end, revising the characteristics of tsunami and its hazard assessment is an important initiation.

Characteristics of tsunami

The term 'tsunami' comes from Japanese, meaning 'wave in harbour'. Tsunamis are giant waves caused by the sudden displacement of a large volume of water in the ocean. These displacements are most often caused by tectonic movements associated with undersea earthquakes. Others causes of tsunami also include coastal landslides, volcanic eruptions and meteoric impacts.

Regarding tsunami characteristics, tsunami waves move outward from their source region over a long distance in the open ocean without obvious distortion of waveforms (Zhao *et al.*, 2012). Thus, tsunamis cause serious damage not only to neighbouring countries, but also distant countries (Choi *et* *al*., 2016). For example, the undersea earthquake in the Indian Ocean in 2004 caused by the sea-floor subduction generated a massive tsunami, damaging the coastal areas in the region as well as some other countries in Africa.

As a tsunami wave propagates towards the shore, its speed depends upon the depth of the water. The speed decreases as the water gets shallower, and in order to conserve energy, the wave height increases (Aon, 2015). Therefore, when tsunamis reach the shore, the waves temporarily bunch up and increase, and, therefore, travel further inland, a phenomenon known as tsunami inundation (Zhao *et al*., 2012). The bunching-up effect makes tsunami waves flood the land at the highest elevation known as tsunami run-up. The below Figure illustrates the characteristics of tsunami waves reaching the shore and following inundation distance and run-up elevation.

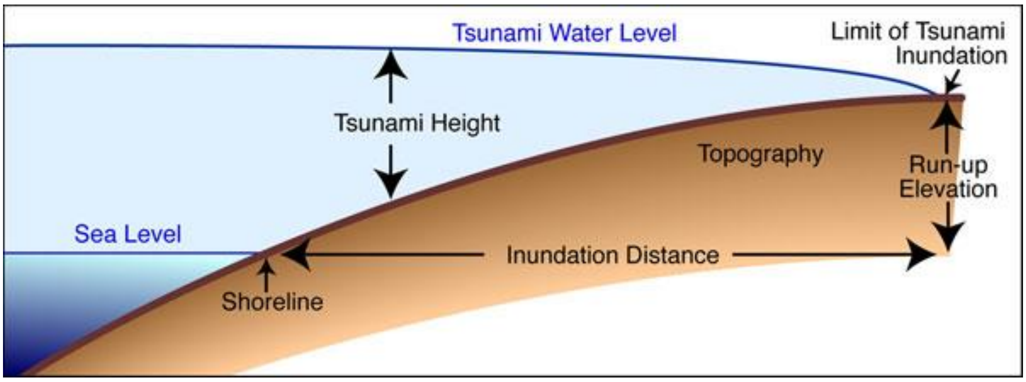


Figure: Characteristics of tsunami inundation and run-up.

Source: U.S. Geological Survey, 2018

In the case of the 2004 tsunami, the highest tsunami run-up near Banda Aceh, the most seriously hit area in Indonesia, reached as high as 48 metres, while run-up heights of up to 10 metres in Thailand were recorded (Aon, 2015). This was to be expected since Indonesia was very close to the tsunami source.

However, Titov *et al.* (2005) argues that the 2004 tsunami was very directional in the east-west path because of the characteristics of the undersea plate subduction. This explains why Somalia, which was far to the east of the tsunami source, received greater damage than Bangladesh, which lies to the north of the tsunami epicentre, even though Bangladesh was closer to the tsunami source than Somalia. Thus, in addition to distance from the tsunami source, the direction of location associated with the source is another factor that can affect the extent of tsunami impact.

Thailand lies to the east of the potential subduction zone which caused the 2004 earthquake and subsequent tsunami. Thus, if a tsunami occurs in the same region, the country may receive a great impact due to the characteristics of the tsunami-triggered direction. It is, therefore, essential that the Thai authorities focus on developing mechanisms to deal with a large-scale tsunami in every disaster phase.

In the matter of damage and destruction from tsunamis, the direct consequences are basically dependent on three factors: inundation, wave impact on structures and erosion (IOC, 2008). These impact factors can lead to death and injuries caused by wave force, debris and pollution, for example. Thus, development of a tsunami vulnerability model in the tsunami-prone area may lessen the opportunity for tsunami effects. The model may differentiate between risky and safe areas so that they can be managed in order to cope with a tsunami. For example, Thailand uses the 2004 event as an historical model to identify areas and populations at risk, and, therefore, warning systems and evacuation structures have been established thereafter. This may be very useful for a coastal community in terms of tsunami preparedness. Emphasising tsunami hazard assessment is, therefore, essential for coastal communities, especially in a tsunami-prone area.

Tsunami hazard assessment

Tsunami hazard assessments focus on characterising and visualising the physical characteristics of future tsunamis, such as a potential inundation area that can present a threat to people (National Research Council, 2011). Thus, documentation of tsunami hazards for a coastal community is needed to estimate the extent of risk and consequence in the area. This assessment requires information of possible tsunami sources, such as an earthquake hazard zone (IOC, 2008).

The characteristics of tsunamis from the sources at different locations along the coast also are essential to be considered when assessing a tsunami hazard. For those communities, data and earlier tsunamis may help quantify these factors. For most communities, however, only very limited or no historical data exists. For example, Murthy *et al.* (2011) claim that assessing the tsunami hazard on the Indian coastal areas presents a scientific challenge because of the lack of both historical events and data. As a result, developing methodology and technology for tsunami hazard evaluations can provide useful information to such communities so that preparedness, response plans and mitigation strategies can be systematically developed. In order to gain development direction, tsunami hazard assessments basically encompass three elements given by National Research Council (2011);

- Inundation models to determine the areas likely to be flooded.
- Hazard maps that describe inundation-model outputs on community base maps, e.g. roads, elevation and structures.
- Evacuation maps that represent safe areas in which people may need to be evacuated in the event of tsunamis.

As a consequence, in recent years, many researchers have paid attention to tsunami studies focusing on a tsunami hazard assessment (e.g. Zahibo and Pelinovsky, 2001; Hébert *et al.*, 2001; Legg *et al.*, 2003; Kulikov *et al.*, 2005). Of these studies, much effort has been put into the development of methods, data and techniques for tsunami risk assessment and for creating new technologies for tsunami impact mitigation (Strunz *et al.*, 2011; Basher, 2006; Post *et al.*, 2008). These studies provide comprehensive analyses of tsunami risk, emphasising the potential of applying remote-sensing techniques as a tool for supporting risk assessment on regional and local scales.

In most of the literature that studies tsunami hazard assessments, some common outputs are in the form of thematic risk maps (e.g. tsunami risk map, death rate distribution map, evacuation map), tables or graphs (Jelínek *et al.*, 2012). For example, Post *et al.* (2008) study tsunami risk in Indonesia, and the results are provided as thematic maps and GIS information layers for the national and regional planning institutes.

Moreover, tsunami risk assessments found in the literature are generally performed using either a probabilistic or deterministic approach. The probabilistic method provides a more realistic picture of the risk to the investigated area, and has a higher significance for planning effective countermeasures (Jelínek *et al.*, 2012). However, more effort has been put into the understanding of tsunami hazards than into estimating the potential impacts on people and infrastructure (Wood, 2007; Jelínek *et al.*, 2012).

Assessing tsunami hazards can result in evaluating the identification of tsunami prone-areas and vulnerable people. Thus, such variables can become the key factor for the logistics design. Accordingly, it is necessary to review the literature on the aspect of humanitarian logistics in the next section.

Appendix C

Foundation of Humanitarian Logistics

Humanitarian logistics term

The term "humanitarian logistics" today is discussed more often among both academia and professionals. Thus, it is important to clarify its meaning and to discuss the importance of humanitarian logistics and the differences between humanitarian and commercial logistics.

Thomas and Kopczak (2005) define humanitarian logistics as "*…the activities of planning, implementing and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of alleviating the suffering of vulnerable people.*"

Van Wassenhove (2006) proposes "*…for humanitarians, logistics is the processes and systems involved in mobilizing people, resources, skills and knowledge to help vulnerable people affected by disaster.*"

According to these definitions, humanitarian logistics focuses on the moving of resources to and casualties from a disaster area with efficiency and effectiveness. With limited resources and time, humanitarian logistics seems to be the most vital challenge of applying the concept of logistics.

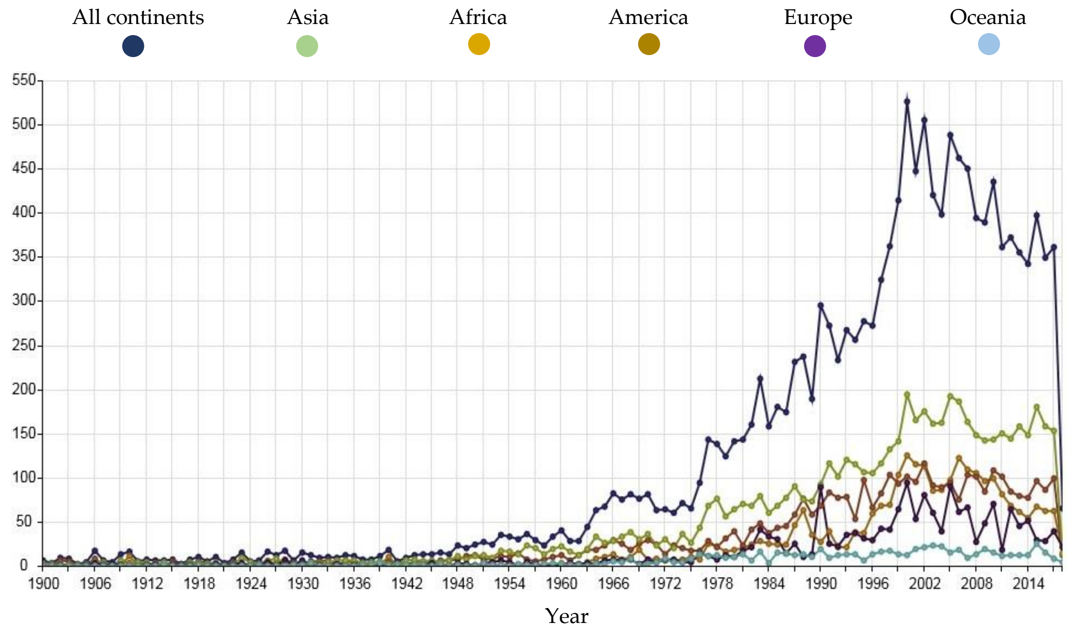
The need for humanitarian logistics

To answer the question why one should improve humanitarian logistics, it is worth noting that natural disasters have been occurring increasingly across the world. According to the international disaster database EM-DAT, the number of disasters has increased over the past century. Figure (a) shows the number of natural disasters per continent between 1900 and 2018, while Figure (b) illustrates the total affected persons per disaster type in the same period.

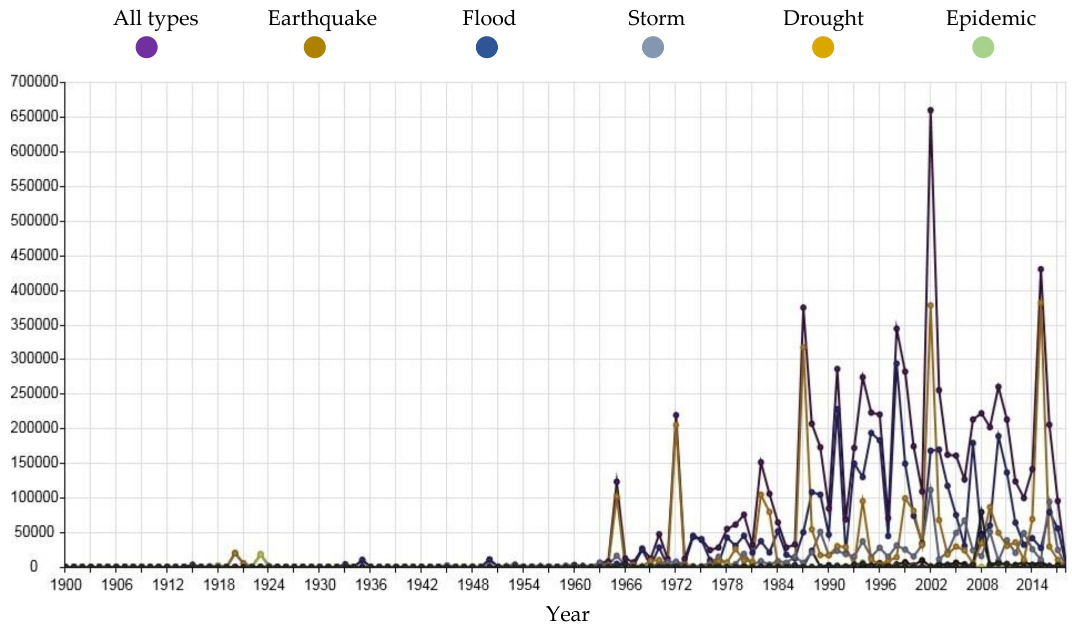
According to Figure (a), the trend of the number of disasters has increased dramatically during the past 40 years (1978–2018). The Asian region had the largest number of disasters in that period, followed by Africa, America and Europe, respectively. As a result, the need for disaster relief will keep growing due to the increasing number of disasters (Thomas and Kopczak, 2005).

Figure (b) shows that earthquakes and floods, which usually leave a vast number of people affected resulting in an urgent need of humanitarian response, are the most frequently occurring disasters compared to other types. This information indicates that humanitarian logistics is a significant relief activity that needs greater attention from humanitarian organizations to enhance logistics mechanisms, particularly in dealing with such sudden-onset natural disasters.

According to the disaster literature, Van Wassenhove (2006) insists that logistics is the most vital part in humanitarian aid operations because their success or failure is dependent on the logistics performance. As can be seen from the consequences of the 2004 tsunami in the Indian Ocean, agencies providing humanitarian relief had to struggle a lot to sort out required goods and distribute them in a timely and economic way (Habib *et al.*, 2016).



(a)



(b)

Figure: (a) Number of disasters per continent, (b) Total affected population per disaster type.

Source: EM-DAT (www.emdat.be)

Yet humanitarian logistics operations faced many hindrances in disasters. For example, in the 2008 Sichuan earthquake, poor road conditions worsened by bad weather and mudslides, and it took several days before rescuers were fully deployed. Furthermore, the 2010 Haiti earthquake disclosed some critical issues regarding humanitarian logistics, such as how to prioritize the use of ramp space at the airport, how to efficiently plan the use of heavy lifting equipment to clear the roads and how to minimize fuel consumption in a road network with uncertain road blockages, etc.

As a result of such disasters, academics and practitioners should concentrate more on the issues faced in humanitarian logistics to have efficient planning and practice in disaster relief operations.

Appendix D

Interview Questions

Visiting the Relief Supply Centre (Regional office no.18 – Phuket)

The Department of Disaster Prevention and Mitigation (DDPM)

Ministry of Interior, THAILAND

This visit aims to obtain the data about both the supply centre itself and the past tsunami relief operation, as well as the current plan for future tsunamis. The data will be collected by the interview approach and from the director of DDPM regional office no.18 Phuket.

The participant:

Mr. Chatchawan Benchasiriwong

The Director of DDPM regional office no.18 Phuket

Department of Prevention and Mitigation (DDPM)

Ministry of Interior, THAILAND

Website: http://www.disaster.go.th/en/index.php

Interview Questions

Part 1: General information

1. What is the nature of the humanitarian disaster that your organization is engaged in?

   Answer: This centre is responsible for all types of disaster including natural and man-made e.g. earthquake, landslide, tsunami, storm, flood, fire, drought, famine, disease epidemic, industrial accident, transport accident, etc.

2. What types of vehicle are located for emergency services at your organization?

   Answer: We have 2 types of vehicles located at the centre. Firstly, the vehicles that are prepared for road transport including 10-wheel truck, pickup truck and fire truck. Secondly, the vehicles that can be used for water transport including rubber boat and motorboat. However, helicopter is now considering to be used for disaster relief operations in the future.

3. What types of relief items are stocked for emergency services at your organization?

   Answer: Very few relief items are stored in the warehouse and they are not perishable items like clothes. Regarding other essential relief items, we have made the agreement to buy and sell with a number of suppliers because perishable items (e.g. medicine, food, water) must be purchased when they are needed. In a relief operation, a set of relief items is usually prepared in the form of survival bag.

4. What is the most common mode of transport used in movement of relief items?

   Answer: Road transport, trucks have been mostly used for the relief operations. If road-transport mode cannot be used in some specific situations like flooding, boats are usually needed to use for the operations.

5. Has the centre adopted transportation optimization models to help in relief delivery at the minimum cost?

   Answer: There is no existing development.

Part 2: The 2004 tsunami relief

1. Did you have decision-making mechanisms in place for the relief operation?

   Answer: Yes.

   If yes, please give examples:

   The mechanism was using hierarchical social order. For example, the locations and the number of people affected were originally communicated from people who were in the scene to the subdistrict municipality. In turn, the municipality reported to the district office from which the centre received the information about the situation. Then, the centre operated the relief logistics for the beneficiaries with the information provided hierarchically.

2. Did you use any technological tools to support the relief operation?

   Answer: Yes.

   If yes, please give examples:

   In the aftermath of the disaster, only radio communication was used in the relief operations. Most telephone networks were not available due to the disaster consequences.

3. Did you face resource limitations while running the relief operation?

   Answer: Yes.

   If yes, please give examples:

   In the aftermath of the disaster, there were so many people affected by the tsunami, and therefore relief items were not prepared for that large number resulted in delivery delays. Also, due to the chaos and many affected locations, there was a lack of vehicles for delivering relief goods to the casualties.

4. Did you experience any delays in delivering supplies to beneficiaries?

   Answer: Yes.

   If yes, what were the causes of delays?

   There were delays of shipping relief goods to the scenes due to the massive sufferers. Moreover, uncertain number of those affected caused delays because there was no an efficient algorithm for relief routing i.e. the order of location visiting. This led the trucks had many trips for transporting goods resulted in the delays of the distribution.

5. Did you experience any blocked delivering routes as a result of the disaster?

   Answer: Yes.

   If yes, what were the actions then?

   In the aftermath of the disaster, many roads and infrastructure near the coastline were devastated by the disaster resulted in the difficulties of relief delivering. However, this problem is expected to be a minor concern in the future due to the preparation of evacuation shelters to which road transport can be accessed.

6. Were you able to deliver relief items to the right place that they were needed?

   Answer: Yes, the affected locations were reported from the district office as mentioned earlier. However, the affected people were met in various random directions.

7. Were you able to deliver the items to the deadlines that they were needed?

   Answer: Yes, the relief deliveries were done in the 72 hours after the tsunami strike. However, if there was another tsunami the first delivery should be done within 24 hours.

8. Were you able to deliver the right quantity of items to the beneficiaries?

   Answer: No, as mentioned earlier, the demand of each affected locations was uncertain. The casualties were estimated from the hierarchical report, but there was an increasing swings in people affected in the scene. This caused difficulties of shipping the relief goods at the right quantity.
9. What were the major logistics problems that occur in relief operation?

   Answer: Lack of technology, no relief logistics plan for tsunami situation, inefficient mechanism for estimating the demand
10. If there was a tsunami in the future, what type of vehicle would be used for delivering relief items to beneficiaries? What is the vehicle capacity for loading the items? and if roads are unusable, which mode(s) of transport would be considered?

    Answer: 10-wheel trucks will be mostly used for delivering relief items to beneficiaries. Each truck has a 5,000 capacity of relief bags. In the future, helicopter may be very useful if roads are unusable, but it is still in consideration due to the cost concern.

Part 3: The emergency plan for future tsunamis

1. Do you have the identified points for evacuation if a tsunami warning is issued?

   Answer: Yes, evacuation points have been predefined around Phuket Island according to the emergency plan for tsunami in Phuket.

2. Do you have the planed routes for relief logistics from your supply centre to those evacuation points if a tsunami hits your responsible area?

   Answer: Yes, as the evacuation locations have been defined and so we can plan the routes to get there.

3. Do you have any approach for identifying the relief item quantities in order to meet beneficiary demands after the strike of a tsunami?

   Answer: Yes, but it is still the same mechanism as used in the 2004 tsunami: hierarchy report from the subdistrict to the centre. However, using only this approach may be insufficient as the demand can be stochastic.

4. Do you have a deadline for delivering relief items to those affected by a tsunami?

   Answer: Yes, the first delivery should be shipped to the beneficiaries within 24 hours.

5. What are your current technologies that will be used for coping with future tsunamis?

   Answer: The tsunami warning system has been installed along the tsunami prone area. Also, if there was a tsunami, the National Disaster Warning Center can estimate the magnitude of a tsunami that, in turn, can approximate the area to be affected.

6. In your opinion, what extent do you agree regarding the relief logistics problem in a tsunami incident (Give 1 to the most important)?

    4 The uncertainty of where to deliver relief items to beneficiaries

    1 The uncertainty of relief items quantity to meet beneficiary demand

    2 The uncertainty of transport time from the centre to the points of evacuation

    3 The uncertainty of routes for using to make the delivery

    no If there is another issue please identify

7. What technology or innovation would you like to have and implement for using in relief logistics in tsunami disasters?

    Answer: Truck tracking system, satellite technology, and other essential decision-making tools

Part 4: To what extent do you reckon about relief operation perspective before and after the 2004 Thailand tsunami event (Use the scale 1 = very small, 2 = small, 3 = moderate, 4 = great, and 5 = very great)

Tsunami relief operation perspective	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Before the 2004 disaster					
The organization had an emergency plan to cope with a tsunami disaster					/
The organization had the planned routes for approaching the affected area					/
The organization faced demand uncertainty while responding to the relief operation					/
The organization faced service-location uncertainty while responding to the relief operation					/
The organization faced travel time uncertainty while responding to the relief operation				/	
The organization faced the lack of transportation resources for the relief operation					/
The organization faced spatial problems (e.g. blocked road) while responding to the relief operation					/

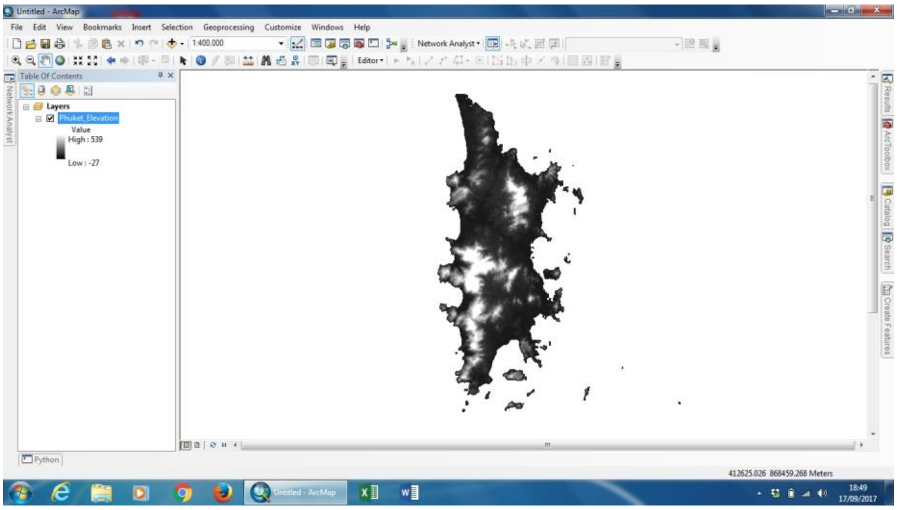
After the 2004 disaster					
The organization recognizes the need for an emergency plan to deal with the next tsunami relief operation					/
The organization recognizes the significant of using innovations and technologies for the next tsunami relief operation					/
The organization recognizes the need for applying geographic information for the next tsunami relief operation					/
The organization recognizes cost reduction and optimization as an important issue for the next tsunami relief operation					/
The organization recognizes a decision-making process as an important mechanism for the next tsunami relief operation					/

Appendix E

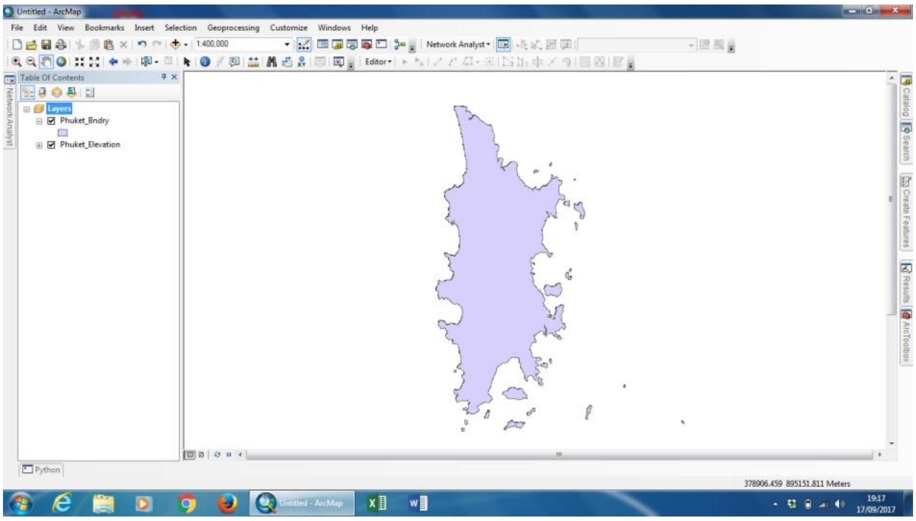
Steps of estimating affected population in the ArcMap environment

1. Preparation stage

1) Prepare DEM of the study area



2) Prepare administrative boundaries of the study area



3) Add new fields to the attribute table of the study area as following stpes

   - Add field [SubDist_POP], and update population data for each sub-district.

   - Add field [Area_Sqkm], and calculate area for each sub-district by using 'Calculate Geometry' function in the attribute table.

   - Add field [POP_Density], and calculate population density for each sub-district by using 'Field Calculator' function in the attribute table. In the field calculator, type [POP_Density] = [SubDist_POP] / [Area_Sqkm].

4) Create urban elevation area by using 'Map Algebra' and 'Raster Calculator' function in the ArcToolbox. In this step, DEM of the study area is used as the source file. In the Expression panel, type (DEM file name) ≤ (*elevation value*). Then, name the DEM output feature.

5) Change the DEM output feature from raster to vector by using 'Raster to Polygon' function in the ArcToolbox. Then, name the output vector feature.

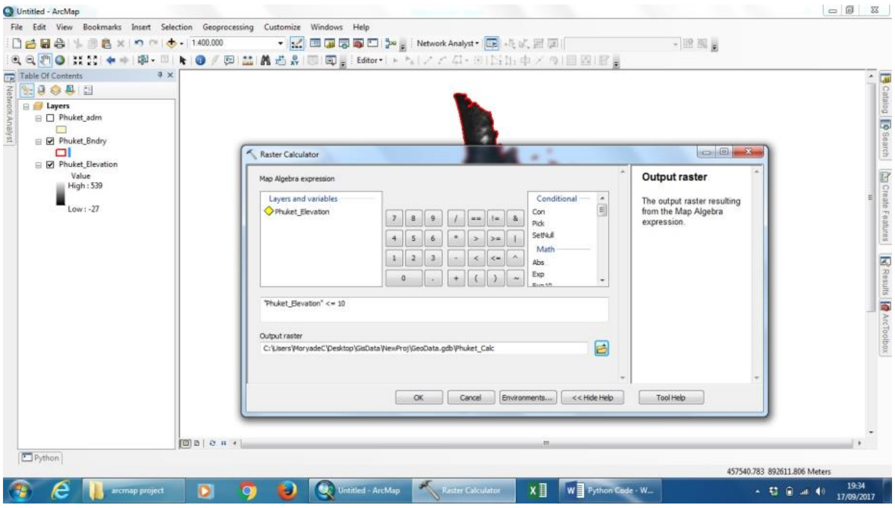
6) Add new fields to the attribute table of output vector feature as following stpes

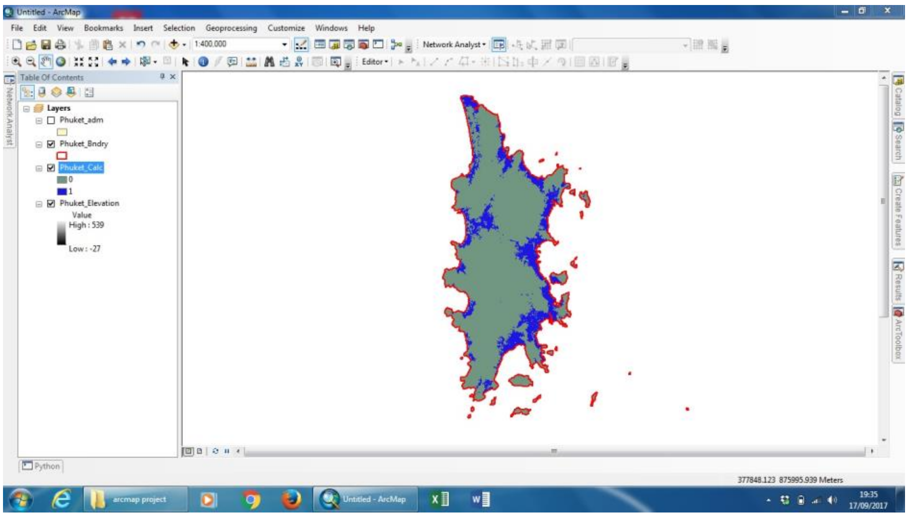
   - Add field [Area_Elev], and calculate area for each sub-district by using 'Calculate Geometry' function in the attribute table.

   - Add field [POP_Elev], and calculate the population figures in each sub-districts by using 'Field Calculator' function in the attribute table. In the field calculator, type [POP_Elev] = [SubDist_POP]* (*population ratio*).

2. Tsunami hazard model stage

1) Select the areas that are lower a tsunami surge by using 'Map Algebra' and 'Raster Calculation' function in the ArcToolbox. In this step, DEM of the study area is used as the source file. In the Expression panel, type (DEM file name) ≤ (*tsunami surge height*). Then, name the DEM output file.

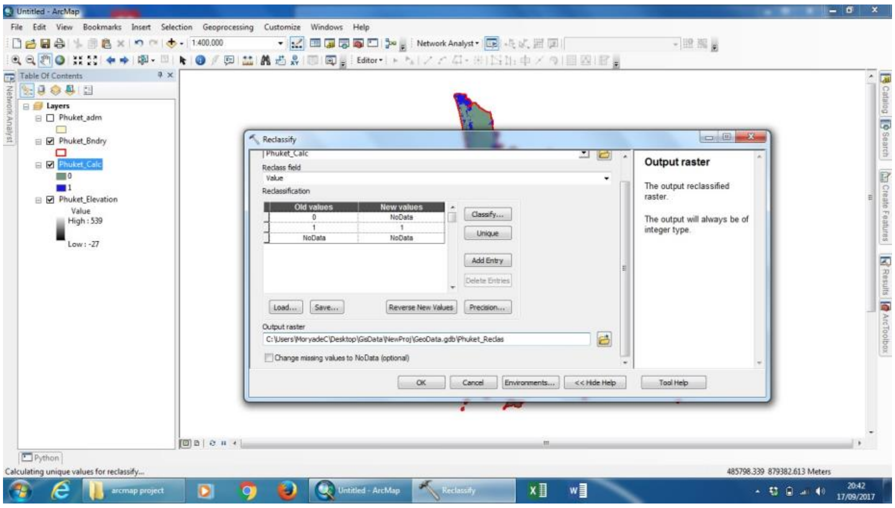


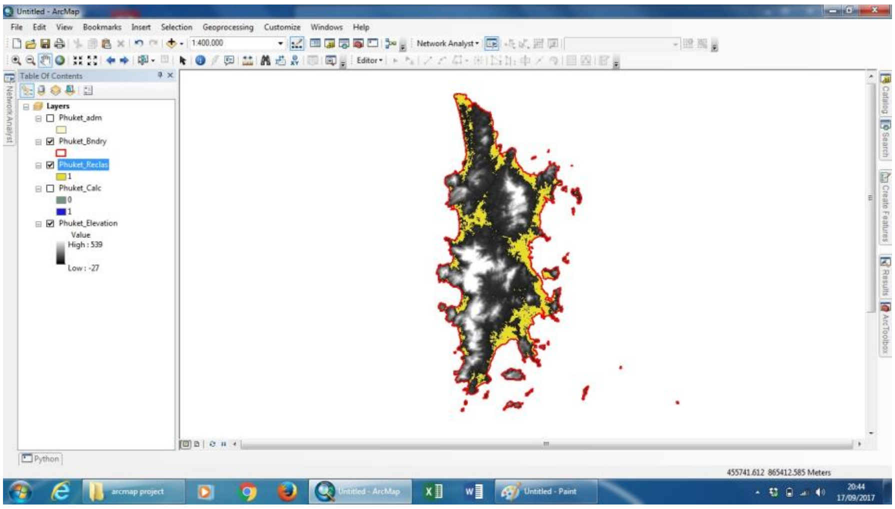


2) Eliminate the areas that are higher than the defined value by using 'Reclassify' function in the ArcToolbox. In the pop-up window, do the following steps.

- In New values entry, change 0 to NoData, and change 2 to 1.

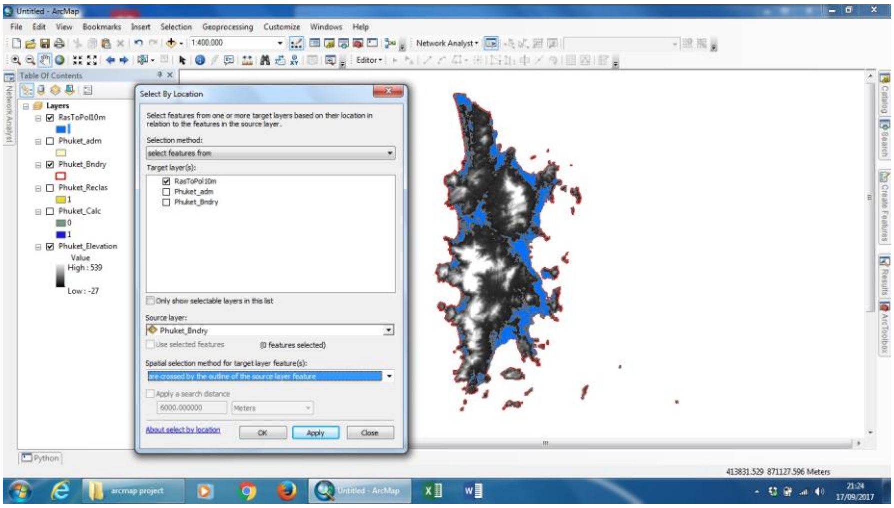
- Name the output DEM feature.

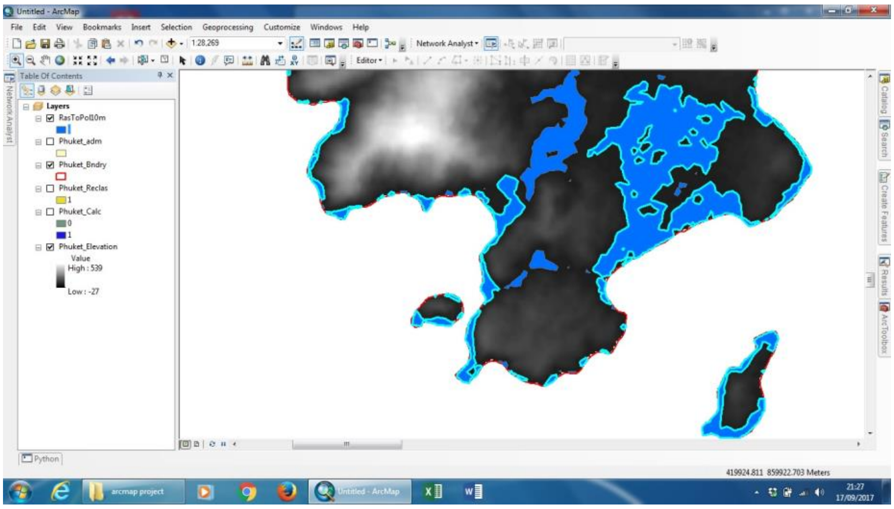


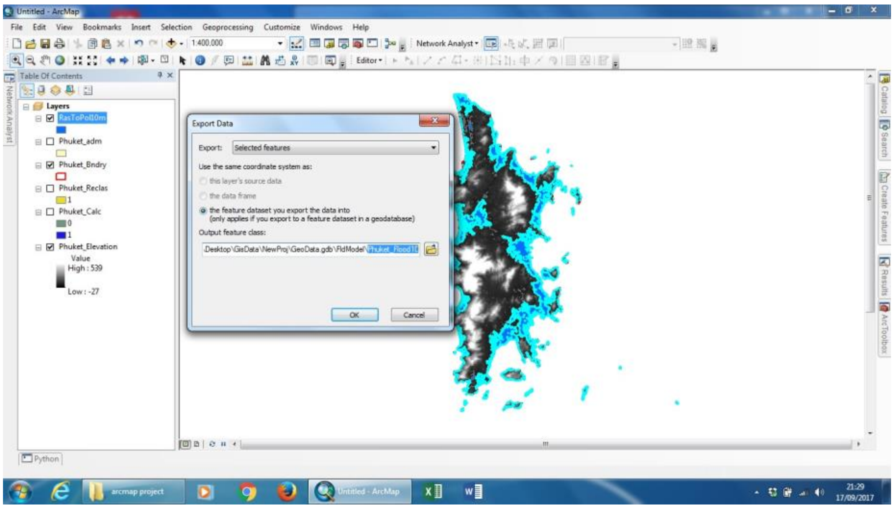


- Change the DEM output feature from raster to vector by using 'Raster to Polygon' function in the ArcToolbox. Then, name the output vector feature.

- Eliminate the flooded areas that are not adjacent to the coastline by using 'Select by Location' function. In the pop-up window, define the output vector feature as the target layer, and select the source layer as the boundary feature of the study area. In 'spatial selection method' option, choose 'are crossed by the outline of the source layer feature'.





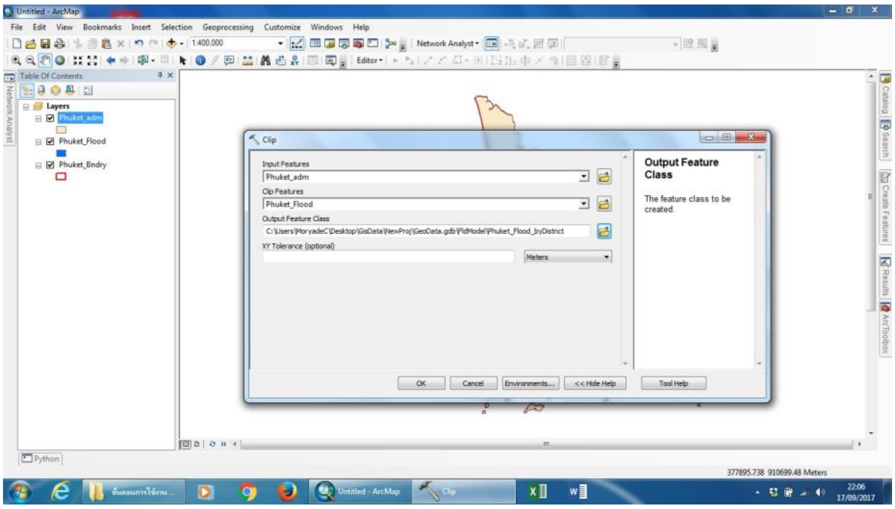


- Export the flood selection and name the output vector feature. This feature contains the flooded area of the study area.

3. Buffer distance stage

1) Define flooded area in each sub-district by using 'Clip' function. To do this, select 'Geoprocessing' and then 'Clip' on the menubar. In the pop-up window, do the following steps.

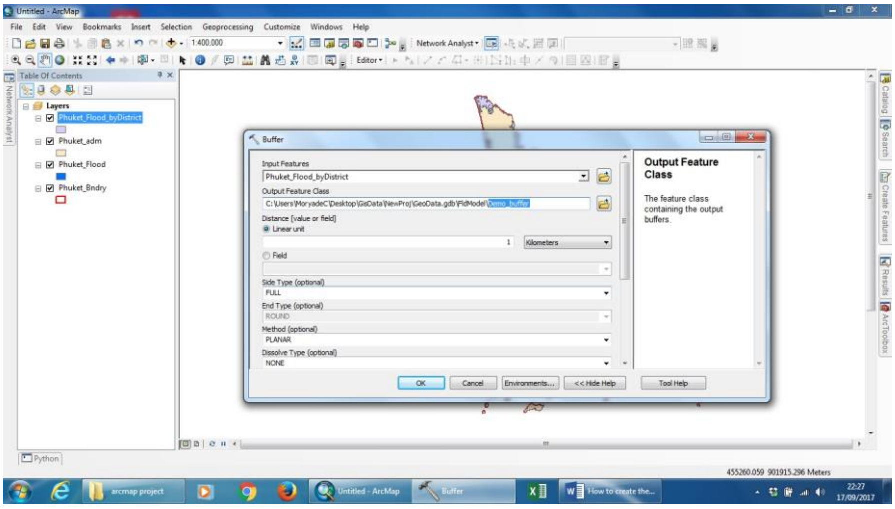
   - Choose the boundary feature of the study area as the input feature.
   - Choose the flooded area feature as the clip feature.
   - Finally, name the output feature.

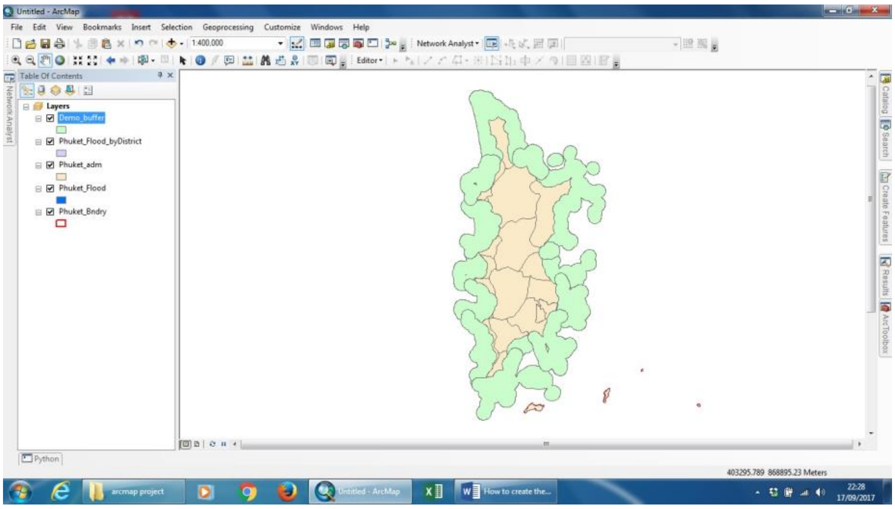


2) Define a buffer area that covers between a buffer line and the flood line in each sub-district by using 'Buffer' function. To do this, select 'Geoprocessing' and then 'Buffer' on the menubar. In the pop-up window, do the following steps.

   - Choose the flooded by sub-district feature as the input feature.
   - Input the following options
     - Distance: input a (*number value*) for a buffer distance.
     - Side Type: choose 'Full'.

- o Name the output feature. Note that this feature covers both sides of the flood line



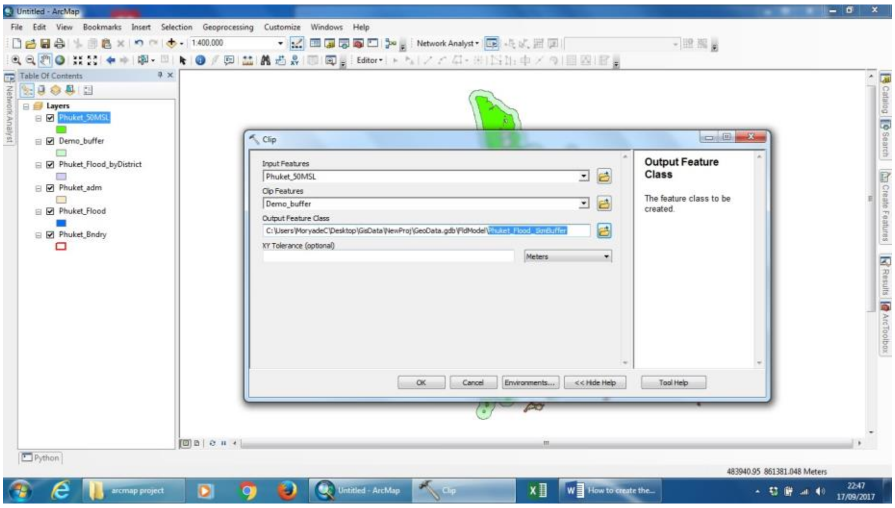


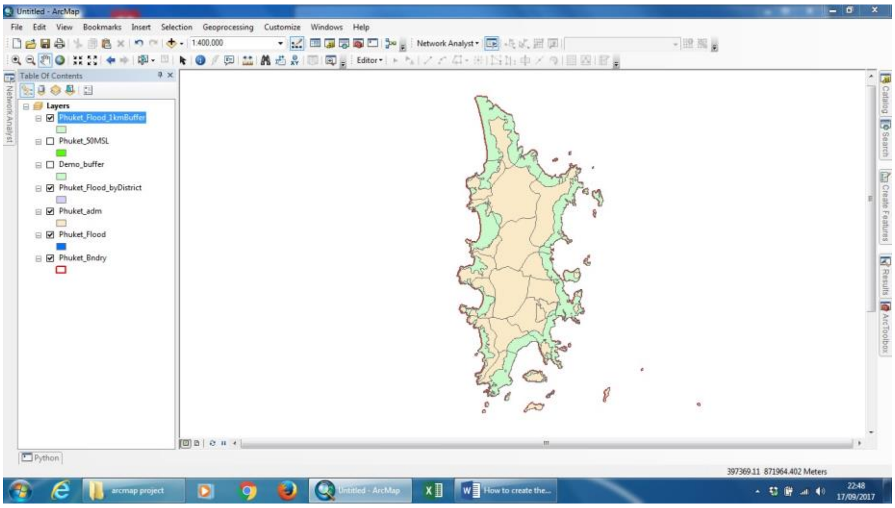
3) Eliminate a buffer area that is not overlapped the study area boundary feature by using 'Clip' function. To do this, select 'Geoprocessing' and then 'Clip' on the menubar. In the pop-up window, do the following steps.

- Choose the elevation feature generated from the preparation stage as the input feature.

- Choose the buffer feature as the clip feature.

- Name the output buffer feature.

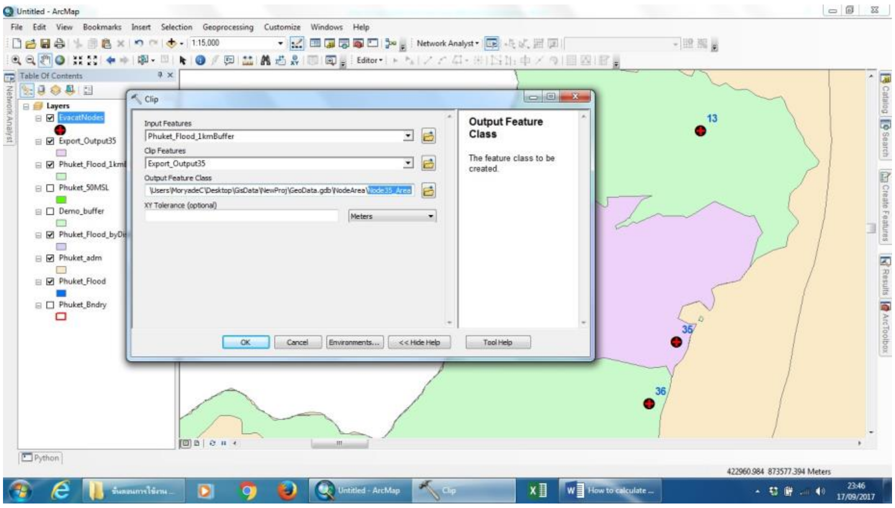


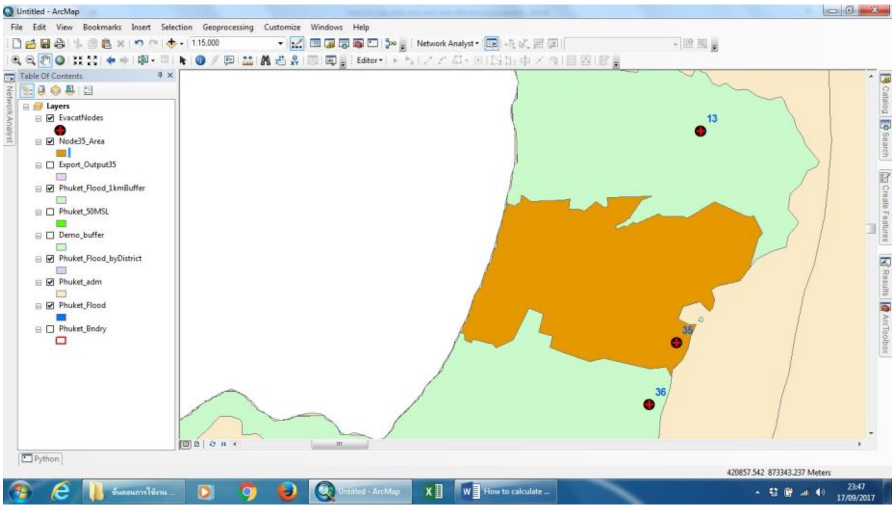


4. Population estimation stage

1) Define affected area in each node service area by using 'Clip' function. To do this, select 'Geoprocessing' and then 'Clip' on the menubar. In the pop-up window, do the following steps.

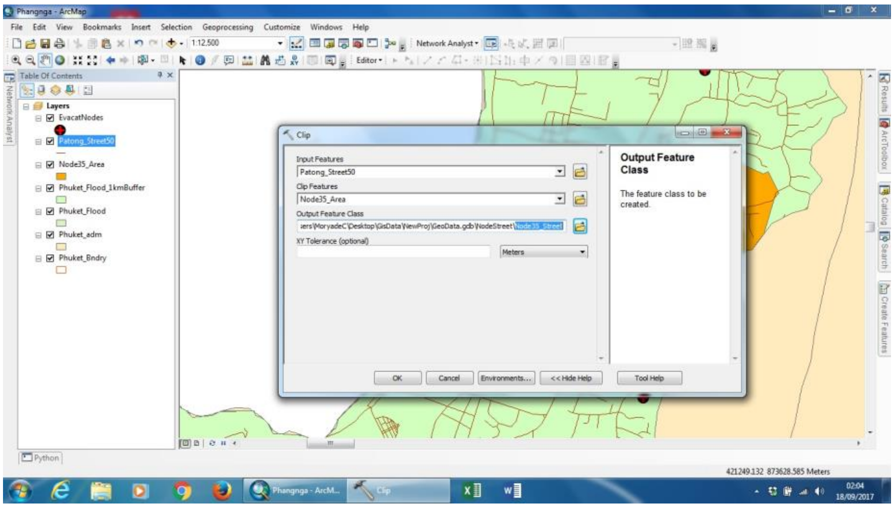
   - Choose the buffer feature as the input feature.
   - Choose a node area feature as the clip feature.
   - Name the output node feature.

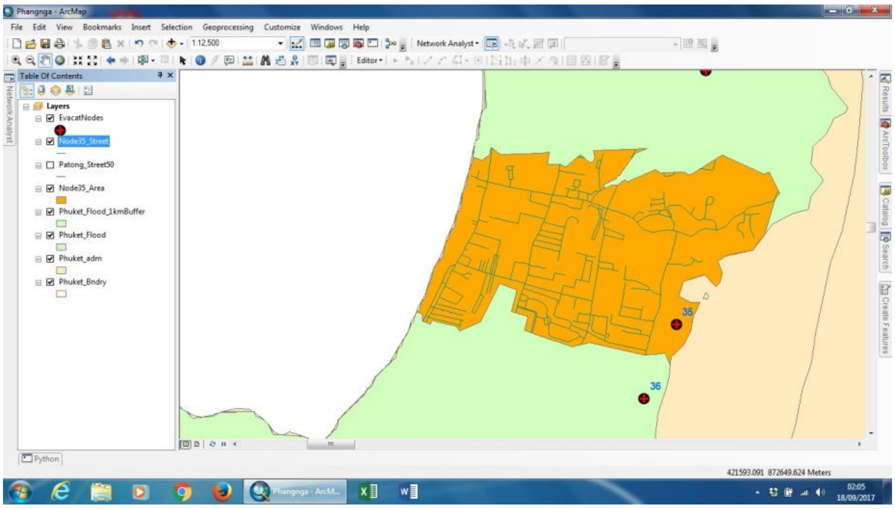




2) Identify a street volume in the node feature by using ‘Clip’ function. To do this, select ‘Geoprocessing’ and then ‘Clip’ on the menubar. In the pop-up window, do the following steps.

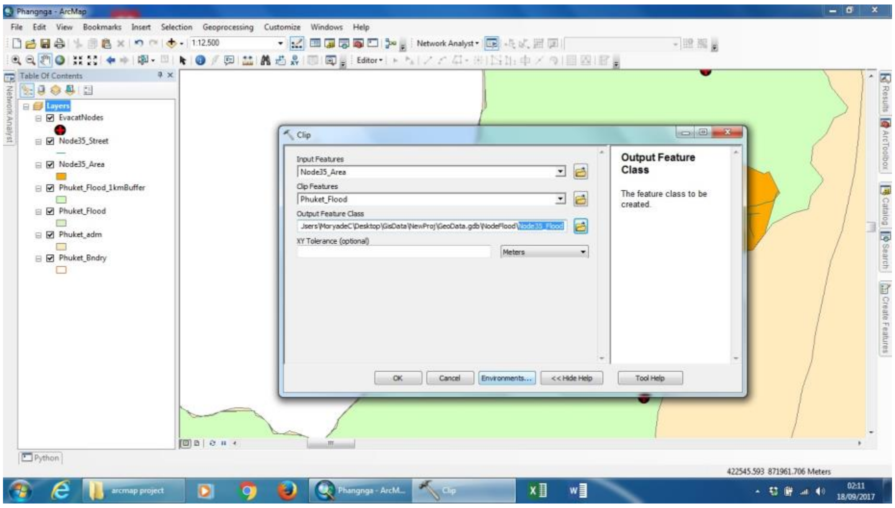
- Choose the street vector feature as the input feature.
- Choose the node feature as the clip feature.
- Name the output node street feature.

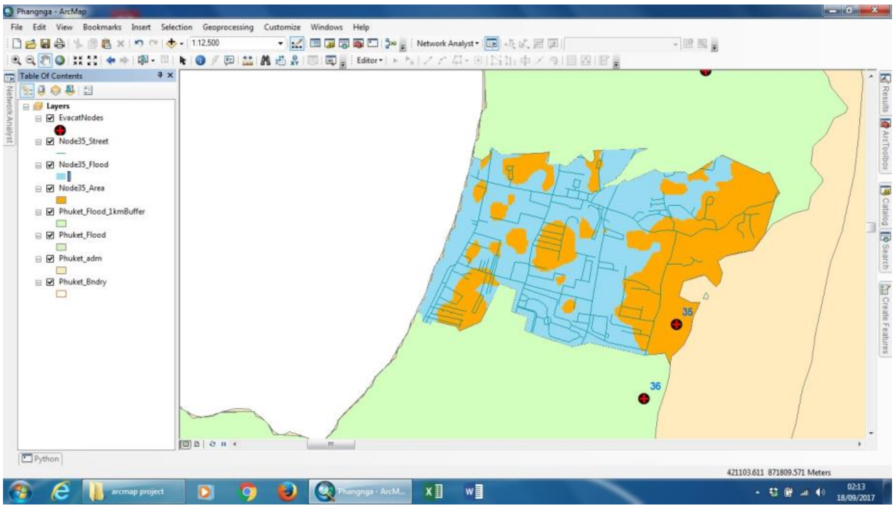




3) Identify a flooded area in the node feature by using 'Clip' function. To do this, select 'Geoprocessing' and then 'Clip' on the menubar. In the pop-up window, do the following steps.

- Choose the node feature as the input feature.
- Choose the flooded area feature as the clip feature.
- Name the output node flood feature.





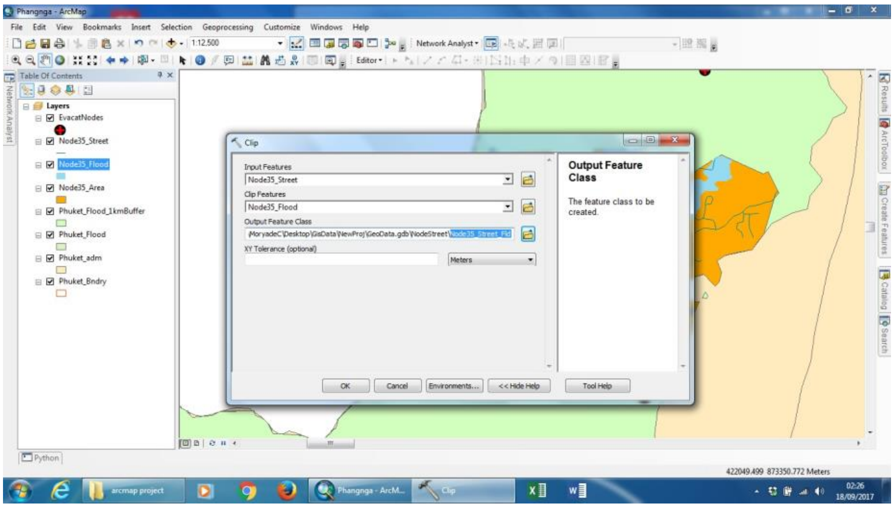
4) In the node flood feature, add field [fArea], and calculate area using ‘Calculate Geometry’ function in the attribute table.

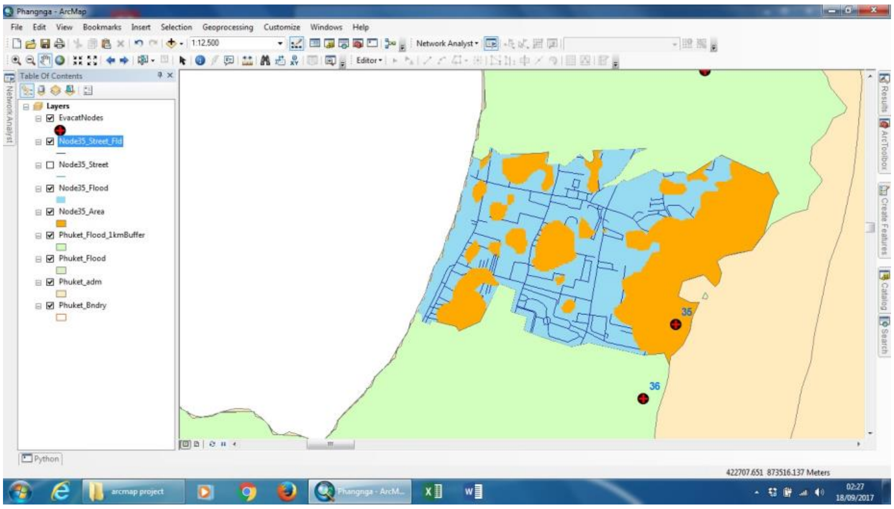
5) Identify a street volume in the node flood feature by uing ‘Clip’ function. To do this, select ‘Geoprocessing’ and then ‘Clip’ on the menubar. In the pop-up window, do the following steps.

   - Choose the node street feature as the input feature.

   - Choose the node flood feature as the clip feature.

   - Name the output node flooded street feature.





6) Calculate a range of affected population by add new fields to the attribute table of node feature as following stpes

- Add field [POPMAX], and calculate the maximum affected population in the node by using 'Field Calculator' function in the attribute table. In the field calculator, type [POPMAX] = [POP_Elev]* ([Node_Street] / [Subdict_Street]).

- Add field [POPMIN], and calculate the minimum affected population in the node by using 'Field Calculator' function in the attribute table. In the field calculator, type [POPMIN] = [POPMAX]* ([Node_FldStreet] / [Node_Street]).

Appendix F

Cost matrix

ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39
1	0	2	9	19	16	15	9	6	5	3	5	21	12	19	22	22	29	39	36	32	28	16	22	26	26	18	15	15	18	17	9	8	20	26	13	13	17	12	13
2	2	0	9	19	16	15	10	7	5	3	5	22	13	20	23	24	30	41	37	33	29	18	24	27	28	20	15	16	18	17	9	8	21	28	14	14	18	12	13
3	9	9	0	12	8	8	15	14	13	11	5	19	10	25	24	29	35	46	42	38	34	22	28	32	32	24	7	12	9	9	2	4	18	32	8	8	11	5	6
4	19	19	12	0	4	12	26	24	23	21	14	31	21	36	36	40	46	57	53	49	45	34	40	43	44	36	19	24	14	9	12	12	29	43	20	20	21	7	7
5	16	16	8	4	0	9	23	21	20	18	11	28	18	33	32	37	43	54	50	46	42	30	36	40	40	32	16	21	12	7	8	9	26	40	17	16	19	4	4
6	15	15	8	12	9	0	22	20	19	17	10	22	14	29	27	34	42	53	49	45	41	30	36	39	40	32	11	16	5	4	8	8	21	40	13	12	13	5	7
7	9	10	15	26	23	22	0	3	13	11	13	19	13	10	13	14	20	31	27	23	19	8	13	17	18	9	16	16	23	24	16	15	19	17	15	15	19	19	20
8	6	7	14	24	21	20	3	0	10	8	10	21	14	13	16	16	23	33	30	26	22	10	16	20	20	12	17	17	23	22	14	13	22	20	16	16	20	17	18
9	5	5	13	23	20	19	13	10	0	3	9	26	16	23	26	26	33	43	40	36	32	20	26	30	30	22	19	19	22	21	13	12	24	30	17	18	22	16	17
10	3	3	11	21	18	17	11	8	3	0	7	24	14	20	24	24	30	41	38	33	29	18	24	27	28	20	17	17	20	19	11	10	22	28	15	16	20	14	15
11	5	5	5	14	11	10	13	10	9	7	0	22	13	23	26	27	33	44	40	36	32	21	26	30	31	22	11	16	13	12	4	3	21	30	12	11	15	7	8
12	21	22	19	31	28	22	19	21	26	24	22	0	10	9	7	13	24	35	31	27	23	19	25	27	29	21	12	7	18	22	21	22	2	21	11	11	14	24	25
13	12	13	10	21	18	14	13	14	16	14	13	10	0	17	15	21	32	43	39	35	31	20	26	30	30	22	3	3	9	13	11	13	8	29	2	2	6	14	16
14	19	20	25	36	33	29	10	13	23	20	23	9	17	0	3	6	16	27	24	19	16	11	17	19	21	13	19	14	25	29	26	25	10	14	18	18	21	29	30
15	22	23	24	36	32	27	13	16	26	24	26	7	15	3	0	8	19	29	26	22	18	14	20	21	24	16	17	12	22	27	26	27	7	16	16	16	19	29	30
16	22	24	29	40	37	34	14	16	26	24	27	13	21	6	8	0	15	26	22	18	14	14	20	18	24	15	24	19	29	34	30	29	14	10	23	23	25	33	34
17	29	30	35	46	43	42	20	23	33	30	33	24	32	16	19	15	0	18	14	10	6	16	10	6	13	14	34	29	40	44	36	35	25	10	33	34	36	39	40
18	39	41	46	57	54	53	31	33	43	41	44	35	43	27	29	26	18	0	4	8	15	30	24	20	27	28	45	40	51	55	47	46	36	18	44	44	47	50	51
19	36	37	42	53	50	49	27	30	40	38	40	31	39	24	26	22	14	4	0	6	12	26	20	17	24	25	42	37	47	51	43	42	32	14	41	41	43	46	48
20	32	33	38	49	46	45	23	26	36	33	36	27	35	19	22	18	10	8	6	0	7	22	16	12	19	20	37	32	43	47	39	38	28	10	36	37	39	42	43
21	28	29	34	45	42	41	19	22	32	29	32	23	31	16	18	14	6	15	12	7	0	18	12	9	15	17	33	29	39	43	35	34	24	4	33	33	35	38	39
22	16	18	22	34	30	30	8	10	20	18	21	19	20	11	14	14	16	30	26	22	18	0	6	9	10	2	23	23	29	31	24	23	20	18	22	22	26	27	28
23	22	24	28	40	36	36	13	16	26	24	26	25	26	17	20	20	10	24	20	16	12	6	0	4	4	5	29	29	35	37	30	29	26	17	27	28	32	32	34
24	26	27	32	43	40	39	17	20	30	27	30	27	30	19	21	18	6	20	17	12	9	9	4	0	7	8	33	32	39	41	33	32	27	13	31	31	35	36	37
25	26	28	32	44	40	40	18	20	30	28	31	29	30	21	24	24	13	27	24	19	15	10	4	7	0	9	33	33	39	41	34	33	30	20	32	32	36	37	38
26	18	20	24	36	32	32	9	12	22	20	22	21	22	13	16	15	14	28	25	20	17	2	5	8	9	0	25	25	31	33	26	25	22	19	24	24	28	29	30
27	15	15	7	19	16	11	16	17	19	17	11	12	3	19	17	24	34	45	42	37	33	23	29	33	33	25	0	5	6	11	9	10	11	32	2	1	4	12	13
28	15	16	12	24	21	16	16	17	19	17	16	7	3	14	12	19	29	40	37	32	29	23	29	32	33	25	5	0	11	15	14	16	6	27	4	5	7	17	18
29	18	18	9	14	12	5	23	23	22	20	13	18	9	25	22	29	40	51	47	43	39	29	35	39	39	31	6	11	0	5	10	12	16	37	8	8	8	9	10
30	17	17	9	9	7	4	24	22	21	19	12	22	13	29	27	34	44	55	51	47	43	31	37	41	41	33	11	15	5	0	10	10	20	41	12	12	12	7	7
31	9	9	2	12	8	8	16	14	13	11	4	21	11	26	26	30	36	47	43	39	35	24	30	33	34	26	9	14	10	10	0	2	19	34	10	10	13	5	6
32	8	8	4	12	9	8	15	13	12	10	3	22	13	25	27	29	35	46	42	38	34	23	29	32	33	25	10	16	12	10	2	0	21	33	12	11	14	5	7
33	20	21	18	29	26	21	19	22	24	22	21	2	8	10	7	14	25	36	32	28	24	20	26	27	30	22	11	6	16	20	19	21	0	22	10	10	12	22	24
34	26	28	32	43	40	40	17	20	30	28	30	21	29	14	16	10	10	18	14	10	4	18	17	13	20	19	32	27	37	41	34	33	22	0	31	31	33	36	38
35	13	14	8	20	17	13	15	16	17	15	12	11	2	18	16	23	33	44	41	36	33	22	27	31	32	24	2	4	8	12	10	12	10	31	0	0	5	13	14
36	13	14	8	20	16	12	15	16	18	16	11	11	2	18	16	23	34	44	41	37	33	22	28	31	32	24	1	5	8	12	10	11	10	31	0	0	5	13	14
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38	12	12	5	7	4	5	19	17	16	14	7	24	14	29	29	33	39	50	46	42	38	27	32	36	37	29	12	17	9	7	5	5	22	36	13	13	16	0	2
39	13	13	6	7	4	7	20	18	17	15	8	25	16	30	30	34	40	51	48	43	39	28	34	37	38	30	13	18	10	7	6	7	24	38	14	14	17	2	0

Appendix G

Chapter 6 Experimental Results

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	32.93	4,861	147.58	1 - 32 - 36 - 35 - 1
2	43.90	4,909	111.82	1 - 2 - 11 - 30 - 29 - 3 - 31 - 1
3	36.28	3,989	109.95	1 - 27 - 37 - 1
4	51.50	4,736	91.96	1 - 8 - 14 - 15 - 12 - 33 - 28 - 13 - 1
5	57.73	4,976	86.20	1 - 6 - 38 - 39 - 4 - 5 - 10 - 9 - 1
6	110.20	4,594	41.69	1 - 7 - 16 - 34 - 21 - 20 - 18 - 19 - 17 - 24 - 25 - 23 - 26 - 22 - 1
				Total cost : 332.54
				Resource efficiency : 0.69
				Number of routes : 6

Table 1: Numerical solutions of scenario 1 using parameter $t_l : r_1$.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	35.48	4,277	120.54	1 - 8 - 36 - 35 - 1
2	42.24	4,992	118.18	1 - 30 - 29 - 3 - 31 - 1
3	51.07	4,952	96.97	1 - 33 - 12 - 15 - 14 - 1
4	48.08	4,608	95.84	1 - 6 - 38 - 39 - 4 - 5 - 1
5	26.70	2,493	93.37	1 - 32 - 11 - 2 - 9 - 10 - 1
6	71.89	4,983	69.32	1 - 7 - 16 - 27 - 37 - 28 - 13 - 1
7	103.98	4,891	47.04	1; 22; 26; 23; 25; 24; 17; 19; 18; 20; 21; 34;
				Total cost : 379.44
				Resource efficiency: 0.79
				Number of routes : 7

Table 2: Numerical solutions of scenario 2 using parameter $t_l : r_2$.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	26.98	4,616	171.06	1 - 35 - 36 - 1
2	31.65	3,553	112.25	1 - 6 - 32 - 1
3	42.36	4,746	112.03	1 - 2 - 11 - 30 - 29 - 3 - 1
4	44.78	4,953	110.61	1 - 8 - 37 - 27 - 1
5	41.37	4,213	101.84	1 - 31 - 38 - 39 - 4 - 5 - 1
6	54.24	4,828	89.01	1 - 10 - 9 - 13 - 33 - 12 - 28 - 1
7	72.69	4,738	65.18	1 - 7 - 15 - 14 - 25 - 26 - 1
8	102.04	4,932	48.33	1 - 22 - 23 - 24 - 17 - 19 - 18 - 20 - 21 - 34 - 16 - 1
				Total cost : 416.13
				Resource efficiency : 0.86
				Number of routes : 8

Table 3: Numerical solutions of scenario 3 using parameter $t_l : r_3$.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	26.70	4,400	164.79	1 - 32 - 11 - 2 - 9 - 10 - 1
2	31.36	4,675	149.10	1 - 3 - 27 - 1
3	26.18	3,058	116.79	1 - 35 - 1
4	40.95	4,538	110.82	1 - 6 - 36 - 1
5	41.37	4,574	110.57	1 - 31 - 38 - 39 - 4 - 5 - 1
6	47.91	4,804	100.26	1 - 30 - 29 - 37 - 1
7	44.24	3,949	89.26	1 - 13 - 33 - 12 - 28 - 1
8	52.60	4,651	88.42	1 - 8 - 14 - 15 - 16 - 7 - 1
9	95.71	4,986	52.10	1 - 22 - 24 - 17 - 19 - 18 - 20 -21 - 34 - 1
10	53.25	1,945	36.53	1 - 23 - 25 - 26 - 1
				Total cost : 460.26
				Resource efficiency : 0.96
				Number of routes : 10

Table 4: Numerical solutions of scenario 4 using parameter $t_l : r_4$.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	10.41	2,461	236.49	1 - 9 - 10 - 1
2	29.46	4,510	153.10	1 - 27 - 1
3	31.65	4,265	134.74	1 - 6 - 32 - 1
4	26.18	3,354	128.10	1 - 35 - 1
5	41.37	4,889	118.18	1 - 31 - 38 - 39 - 4 - 5 - 1
6	42.36	4,933	116.44	1 - 2 - 30 - 29 - 3 - 1
7	37.99	3,947	103.90	1 - 11 - 37 - 36 - 1
8	44.24	4,517	102.10	1 - 13 - 33 - 12 - 28 - 1
9	43.98	4,240	96.41	1 - 8 - 14 - 15 - 7 - 1
10	92.79	4,964	53.50	1 - 22 - 24 - 17 - 19 - 18 - 20 - 21 - 1
11	79.97	3,777	47.23	1 - 26 - 25 - 23 - 34 - 16 - 1
				Total cost : 480.40
				Resource efficiency : 1.00
				Number of routes : 11

Table 5: Numerical solutions of scenario 5 using parameter t_l: r_5.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	26.98	4,361	161.61	1 - 35 - 36 - 1
2	33.68	4,508	133.84	1 - 6 - 3 - 31 - 1
3	36.28	4,832	133.18	1 - 27 - 37 - 1
4	40.98	4,839	118.09	1 - 32 - 38 - 39 - 4 - 5 - 1
5	42.24	4,618	109.31	1 - 2 - 11 - 30 - 29 - 1
6	72.69	4,994	68.70	1 - 7 - 15 - 14 - 25 - 26 - 1
7	44.24	2,727	61.64	1 - 13 - 33 - 12 - 28 - 1
8	111.74	4,699	42.05	1 - 10 - 9 - 22 - 23 - 24 - 17 -19 - 18 - 20 - 21 - 34 - 16 - 8 - 1
				Total cost : 408.84
				Resource efficiency : 0.85
				Number of routes : 8

Table 6: Numerical solutions of scenario 6 using parameter t_h: r_1.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	31.36	4,758	151.75	1 - 3 - 27 - 1
2	32.05	4,142	129.25	1 - 6 - 31 - 1
3	40.59	4,865	119.87	1 - 11 - 30 - 29 - 1
4	40.88	4,372	106.93	1 - 32 - 37 - 36 - 1
5	49.77	4,759	95.62	1 - 5 - 4 - 39 - 38 - 2 - 9 - 10 - 1
6	43.98	3,590	81.63	1 - 8 - 14 - 15 - 7 - 1
7	44.24	3,150	71.20	1 - 13 - 33 - 12 - 28 - 1
8	71.52	4,578	64.01	1 - 26 - 25 - 35 - 1
9	102.04	4,489	43.99	1 - 22 - 23 - 24 - 17 - 19 - 18 - 20 - 21 - 34 - 16 - 1
				Total cost : 456.43
				Resource efficiency : 0.95
				Number of routes : 9

Table 7: Numerical solutions of scenario 7 using parameter t_h: r_2.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	19.81	3,,214	162.27	1 - 31 - 32 - 1
2	29.46	4,518	153.37	1 - 27 - 1
3	40.59	4,922	121.27	1 - 29 - 30 - 1
4	26.18	3,006	114.81	1 - 35 - 1
5	41.13	4,596	111.74	1 - 2 - 11 - 38 - 39 - 4 - 5 - 1
6	32.15	3,465	107.79	1 - 3 - 6 - 1
7	52.60	4,710	89.55	1 - 8 - 14 - 15 - 16 - 7 - 1
8	35.70	3,190	89.35	1 - 36 - 37 - 1
9	44.24	3,863	87.32	1 - 13 - 33 - 12 - 28 - 1
10	62.70	3,708	59.14	1 - 9 - 10 - 25 - 26 - 1
11	95.83	4,894	51.07	1 - 22 - 23 - 24 - 17 - 19 - 18 - 20 - 21 - 34 - 1
				Total cost : 480.38
				Resource efficiency : 1.00
				Number of routes : 11

Table 8: Numerical solutions of scenario 8 using parameter t_h: r_3.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	29.46	4,820	163.62	1 - 27 - 1
2	26.05	3,756	144.19	1 - 10 - 9 - 32 - 1
3	32.47	4,680	144.11	1 - 31 - 3 - 36 - 1
4	37.21	4,889	131.38	1 - 2 - 30 - 6 - 1
5	26.18	3,349	127.91	1 - 35 - 1
6	39.47	4,926	124.80	1 - 11 - 38 - 39 - 4 - 5 - 1
7	44.10	4,728	107.21	1 - 29 - 37 - 1
8	43.98	4,553	103.53	1 - 8 - 14 - 15 - 7 - 1
9	44.24	4,521	102.19	1 - 13 - 33 - 12 - 28 - 1
10	92.91	4,927	53.03	1 - 22 - 23 - 24 - 17 - 19 - 18 - 20 - 21 - 1
11	79.09	3,919	49.55	1 - 26 - 25 - 34 - 16 - 1
				Total cost : 495.17
				Resource efficiency : 1.03
				Number of routes : 11

Table 9: Numerical solutions of scenario 9 using parameter t_h: r_4.

Route priority	Cost (km)	Demand served	Demand-cost efficiency	Nodes visited
1	10.41	2,462	236.58	1 - 9 - 10 - 1
2	19.81	4,510	227.70	1 - 11 - 31 - 32 - 1
3	29.46	5,000	169.73	1 - 27 - 1
4	35.56	4,919	138.35	1 - 6 - 30 - 1
5	36.89	4,454	120.73	1 - 3 - 29 - 1
6	41.13	4,767	115.90	1 - 2 - 38 - 39 - 4 - 5 - 1
7	36.41	4,106	112.76	1 - 13 - 37 - 27 - 36 - 1
8	43.98	4,947	112.49	1 - 8 - 14 - 15 - 7 - 1
9	44.24	4,711	106.49	1 - 33 - 12 - 28 - 1
10	58.15	4,606	79.20	1 - 16 - 35 - 1
11	76.80	4,673	60.85	1 - 22 - 26 - 23 - 25 - 24 - 17 - 34 - 1
12	82.56	4,223	51.15	1 - 19 - 18 - 20 - 21 - 1
				Total cost : 515.39
				Resource efficiency : 1.07
				Number of routes : 12

Table 10: Numerical solutions of scenario 10 using parameter t_h: r_5.