Modelling Spatial Temporal Patterns and Drivers of Urban Residential Fire Risk

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone, the work has not been submitted previously, in whole or in part, to quality for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledge; and ethic procedures and guidelines have been followed.

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2 March 2018

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PUBLICATIONS

Conference Paper

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ABBREVIATIONS

ABS	Australia Bureau of Statistics
AFAC	Australasian Fire and Emergency Service Authorities Council
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AURIN	Australian Urban Research Infrastructure Network
CBD	Central Business District
CFA	Country Fire Authority
DFES	Department of Fire and Emergency Services
FRNSW	Fire and Rescue New South Wales
GDP	Gross Domestic Product
GIS	Geographical Information System
GWR	Geographically Weighted Regression
KDE	Kernel Density Estimation
MFB	Melbourne Fire Brigades
MIF	Mean Information Field
MLE	Maximum Likelihood Estimation
NEXIS	National Exposure Information System
OLS	Ordinary Least Square
QFES	Queensland Fire and Emergency Services
SA1	Statistical Area level 1
SA2	Statistical Area level 2
SA4	Statistical Area level 4
SAMFS	South Australia Metropolitan Fire Services
TFS	Tasmania Fire Services
TOD	Transit-oriented Development
USFA	The U.S. Fire Administration

ABSTRACT

Fire risk, in general, is the probability of a fire occurrence and its potential consequences (e.g. injuries/deaths or financial losses). An exposure to the source of fire ignition such as a live flame or a spark that is further fuelled by the presence of combustible materials, faulty electrical wiring or cooking devices, directly contributes to fire risk. It also hinges on an individual's perception of fire risk, exhibited in situ behaviour such as alcohol drinking habits and the preparedness to respond to threat from fire. More broadly, fire risk is influenced by the size and characteristics of the population at risk or exposed to a fire hazard, and the levels of community resilience, which reflect the sustained ability to utilize available resources to respond to, withstand, and recover from adverse situations. Fire risk, therefore, is difficult to examine as it is driven by a multitude of interwoven factors. There are numerous studies that have applied a range of methods to model fire risk. These methods undoubtedly provide a useful baseline to enhance emergency response and improve resource allocation. Nonetheless, the accuracy, reliability and robustness of these models can be further improved by considering fire risk as a stochastic phenomenon. Furthermore, the role, which space and time plays in shaping fire risk a stochastic process is often overlooked.

The aim of this study was to develop stochastic models to estimate the likelihood of residential fire occurrence and to identify key urban characteristics underpinning fire patterns over time and across space. This study addressed four interrelated key research questions: (i) How does a residential fire pattern occur over time and space? (ii) Can the probability of a residential fire occurrence be predicted as a stochastic process? (iii) How do the urban characteristics impact on residential fire risk? (iv) What spatially-integrated strategies can be developed to mitigate fire risk in an urban setting?

The application of the Markov chain model and Geographically Weighted Regression (GWR) is a key contribution of this thesis because of the novelty of the methodology in quantifying residential fire risk which not only potentially improves the accuracy and reliability of fire risk modelling, but also enriches our understanding of behaviour associated with fire risk in relation to space, time, and situated context at the local level. These models are constructed using residential fire data for the Melbourne Australia, spanning a ten-year period from June 2005 to May 2015.

The key findings demonstrate that, first, the incidence of residential fires across Melbourne during a 10-year period show a higher degree of fluctuation with a strong seasonal variation according to the months of the year. June-August is recorded as having the highest rate whereas March-April and November recorded the lowest rate of fire occurrence. Second, the mapping of the probability of fire occurrence across the Melbourne metropolis shows a city-centric spatial pattern where inner-city sub-regions are relatively more vulnerable to fire than are the outer sub-regions. Third, the time threshold that affects the fire risk levels within a neighbourhood that has had a fire is about two months. When this period of low fire risk elapses, the probability of a fire increases to the normal baseline, equivalent to that in areas with no fire. Fourth, a fire that occurs in a distant area has no significant effect on mitigating fire risk within the neighbourhood. When a distance threshold of 5 km is reached, either one fire or no fire in the past significantly increases the probability of fire. Areas with two or more fires within the neighbourhood are likely to reduce the chance of a fire in the initial period. Fifth, the key findings also reveal that the distribution of residential fires across Melbourne has a complex pattern and is associated with both temporally and spatially-varying neighbourhood attributes. The effect of socio-spatial characteristics such as language, residential mobility, home ownership, type of dwellings, and dwelling density, in relation to residential fires risk tends to be inconsistent across urban areas. Different areas have different contextual situations which influence the level of residential fire risk.

These findings provide new empirical evidence useful for fire agencies seeking to establish appropriate strategies to mitigate adverse impacts of fire on communities. It can also help to identify high fire risk areas and to geo-target when and where to disseminate fire safety information to increase residents' awareness of fire risk.

CHAPTER 1
INTRODUCTION

1.1. INTRODUCTION

Residential fire poses a significant threat to urban communities, particularly for those people who live in high fire risk areas. More than 1,565 residential fires occur every year in the Melbourne Metropolitan area (MFB, 2014), resulting in the loss of lives and causing almost $30 million property damage (MFB, 2014). This cost of residential fires is estimated to equate to approximately 0.07 per cent of Australia's GDP per annum (The Geneva Association, 2014). This places significant economic burden on fire service providers in delivering and maintaining essential services, which are crucial for saving human lives and preventing damage to properties.

Modelling fire risk is a complex process which involves capturing a multitude of interwoven factors underpinning the levels of fire risk for the community. The level of risk is directly influenced by the presence of a source of fire ignition such as a live flame or a spark from faulty electrical wiring or cooking appliances that is further fuelled by combustible materials. It also hinges on an individual's perception, exhibited behaviour and response to threat from fire. More broadly, fire risk, in a geographic sense, is influenced by the size and characteristics of the population at risk or exposed to a fire hazard, and the levels of community resilience, which reflect the sustained ability to utilize available resources to respond to, withstand, and recover from adverse situations.

Most of the previous studies (e.g. Chhetri et al. 2010; Corcoran et al. 2007a; Duncanson et al., 2002; Wuschke et al., 2013) have analysed spatio-temporal fire patterns or their association with individual or neighbourhood characteristics by means of sophisticated statistical and mathematical models and mapping techniques. Although fire risk has recently attracted considerable attention and become the focus of much in-depth analysis, space and time as the two key dimensions of fire risk, and the way they influence fire risk, are still inadequately understood. This gives rise to a key question: how do past fire events within a local area influence the subsequent occurrence of fire incidents?

It is argued that fire risk depends not only on individual-by-individual perception and experience but is also related to how residents' collective perceptions of fire risk within a neighbourhood are linked and connected via complex socio-spatial networks. Perception of fire risk is therefore grounded in space relation, time specificity and the situated context. Space relation plays a vital role in shaping social interaction or the way or modes through which information about fire risk is locally communicated. Space relation is a manifestation of an individual's social interactions within a local community (Bakshy et al., 2012). It shapes the process of "local learning" that occurs within the community. People are more likely to know and retain information about a fire incident when it occurs within their neighbourhood or when they are directly or indirectly affected. This then affect the level of awareness and preparedness to combat a fire or mitigate the risk of fire occurrence.

The perception of fire risk is time-specific. The risk is highly dependent on the ability of people to remember and recall fire incidents which occur within a specified, relatively limited period of time. Thus, memory is partly time-dependent as is the risk perception and behaviour. A fire that has occurred in the immediate past has a greater impact on human behaviour than those that have occurred in the distant past. Space and time are therefore fundamental in shaping the perception and awareness of fire risk. This, in turn, might lead to better prevention and preparedness to help alleviate fire risk.

Fire risk is not only 'space-driven' and 'time-dependent' but is also 'context-specific'. The perception of fire risk in cities is influenced by the spatial variation of the socio-economic and physical characteristics of urban spaces. Factors such as home ownership (DiPasquale and Glaeser, 1999), the length of residence (Pearson et al., 2012), dwelling type (Kennedy, 1978, Pearson et al., 2012), language barrier (Meischke et al., 2010), and socio-economic status (Dekker and Bolt, 2005, Kasarda and Janowitz, 1974), have been found to be the key drivers of fire risk as they affect, if not control, social interactions, local learning and dissemination of risk-related information. Effective risk communication requires a more targeted strategy to reach out to vulnerable communities at greater risk of fire in order to reduce fire risk (Rhodes and Reinholtd, 1998). This thesis, therefore, develops a comprehensive framework for fire risk by considering space-dependency, time-specificity and the context in which a fire occurs.

Space and time dimensions and situated context are not only vital for theory building but also critical to addressing key policy questions. In order to mitigate fire risk, it is important to know the time threshold within which fire incidents can be recalled and behaviour to cope with a fire incident is adjusted. Furthermore, emergency planners would benefit from knowing the effect of distance beyond which the impact on fire risk becomes negligible. This knowledge would help in the planning and implementation of education programs in areas where and when they are needed. There is currently limited empirical knowledge about the effects of space and time on the perception of fire risk. The aim of this study, therefore, is to advance the knowledge in this field by developing a spatio-temporal model to quantify the residential fire risk.

This chapter presents the details of this study, including the aim, research questions, and scope of the study. The chapter consists of six sections. Section 1.2 describes the aim and research questions. The rationale for the study is explained in Section 1.3. Section 1.4 describes the study context and is followed by the structure of the thesis in Section 1.5. Section 1.6 summarises and concludes this chapter.

1.2. AIM AND RESEARCH QUESTIONS

This study aims to develop a stochastic model to estimate the likelihood of residential fire occurrence and to identify key urban characteristics underpinning fire patterns over time and across space using Geographically Weighted Regression. To achieve the research goal, the following research questions were addressed:

1) How does a residential fire pattern occur over time and space?
2) Can the probability of a residential fire occurrence be predicted as a stochastic process?
3) How do urban characteristics impact on residential fire risk?
4) What spatially-integrated strategies can be developed to mitigate fire risk in an urban setting?

1.3. RATIONALE

Residential fire risk is rising globally, and the costs of residential fire-related hazards are mounting (Association, 2014, Ashe et al., 2012). Consequently, this presents significant planning challenges for fire agencies and emergency planners who need to respond efficiently and effectively to threats from fires in a metropolitan setting. Although direct and indirect costs are difficult to estimate, there are three cost components, which indicate the extent of the impact of residential fire on the local community. These are: injuries and loss of human lives; economic costs; and damage to properties. These are discussed below.

1.3.1. Human fatalities and injuries

Residential fires can cause severe social and economic losses. During 2010 – 2014, in India, Russia, and Pakistan, the total number of fire deaths amounted to 10,000 – 25,000 people per year. In comparison to residential fire losses in the world, the consequence of residential fire in Australia is fatal. There are, on average, 100 – 200 fire deaths per year (see Table 1-1). In 2013 – 2014, the Australasian Fire and Emergency Service Authorities Council (AFAC) recorded that, on average, 98 people die in accidental house fires each year.

Table 1-1: Number of fires per year and number of fire deaths per year in Countries in 2010 – 2014 (Brunshlinsky et al., 2016)

	Number of fire deaths per year			
Number of fires per year	**10,000 – 25,000**	**1,000 – 10,000**	**200 – 1.000**	**100 – 200**
600,000 – 1,500,000		USA		
100,000 – 600,000	Russia, India, Pakistan	China	UK, Germany, Brazil, Mexico, Poland	Australia
20,000 – 100,000		Japan, South Africa, Ukraine	Indonesia, Turkey, Canada, Spain, Iran	
10,000 – 20,000			Uzbekistan, Romania, Kazakhstan	Czech Republic
5,000 – 10,000			Philippines	Sri-Lanka

These figures are not surprising given that, on average, over 3.8 million fire-related incidents occur per year around the world. Hence, some countries may have 30,000 – 50,000 fires per year. According to the World Fire Statistics of 2016 published by (Brunshlinsky et al., 2016), Australia had, on average, 100,000 – 600,000 fire-related incidents per year during the period 2010 – 2014 (see Table 1-1). In 2013 – 2014, Australian fire agencies attended 101,867 fire-related incidents, 19 per cent (19,542 incidents) of which were structure fires. However, the report also noted that the number of fires and fire-related fatalities tended to decrease each year.

The scale of fire incidents in Australia however varies across different States and Territories. In New South Wales, there were 23,766 fires during 2010 – 2015 (FRNSW, 2016). In Queensland, the fire agencies attended about 2,400 residential fires per year (QFES, 2016). This was a 9.7 per cent increase during a five-year period from 2002 to 2007. In South Australia, the average number of residential fires is about 1175.6 fires per year (SAMFS, 2016). In 2013 – 2014, the Tasmania

Fire Service recorded 631 residential fires across the region (TFS, 2016). During the same period, about 3,000 residential fires occurred in Victoria (MFB, 2016). The Western Australia Department of Fire and Emergency Services recorded about 60.27 fires per 100,000 households during the 2014 – 2015 period (DFES, 2016).

Within the Melbourne region, in particular, there is evidence that the number of fires attended per annum is on the rise. According to figures from the Metropolitan Fire Brigade (MFB), the incidence of attended fires in Melbourne's residential dwellings increased, despite fire safety campaigns within the community (MFB, 2016). In fact, in 2015 there were 3,211 house fires, up from 3,170 in 2014. The number of residential fires in Melbourne increased more than the overall population growth (5.6%) and more than the number of occupied dwellings (10.7%).

1.3.2. Economic losses

Fire-related damage to properties and structures is likely to be high. During 2008 – 2010, the total direct fire-related losses in the United States were approximately US$13,000 million per year, while in Japan, the total direct losses amounted to US$5,548 million per year and in the United States, it was US$1,750 million (Association, 2014). On average, the economic statistical evaluation of direct fire losses in each country is 0.12 per cent of GDP (Association, 2014, Brunshlinsky et al., 2016). Australia had, on average, US$885 million per year of total direct losses or an average of 0.07 per cent of annual GDP. Although there is limited data on the overall figures for fire losses world-wide, there is evidence that residential fires continue to have an economic impact every year (see Table 1-2).

Table 1-2: Economic-statistical evaluation of fire direct losses, 2008 – 2010
(In millions, except for Japan – billions) (Brunshlinsky et al., 2016, Association, 2014)

Country	**Currency**	**Direct Losses**			**Percentage of GDP**
		2008	**2009**	**2010**	**2008 – 2010**
Hungary	Ft		580	210	0.02 (2009 – 2010)
Singapore	$S	110	115	115	0.04
Slovenia	SIT				0.07 (2002 – 2004)
Australia	$AUS	1,000	955	940	0.07
Czech Rep	KC	3,700	2,450	2,200	0.07
Spain	€	910			0.08 (2008)
Poland	Zl	1,450	1,150		0.09 (2007 – 2009)
United States	$US	17,500	14,000	13,000	0.10
Japan	¥	615	610	565	0.12
New Zealand	$NZ	240		210	0.12
Germany	€	2,850	2,950	2,700	0.12

Country	Currency	Direct Losses			Percentage of GDP 2008 – 2010
		2008	2009	2010	
United Kingdom	£	1,950	1,750	1,750	0.13
Netherlands	€	1,050	925	675	0.15
Finland	€	305	280	330	0.17
Sweden	Kr	5,950	5,550	5,650	0.18
Denmark	Kr				0.20 (2005 – 2007)
France	€	4,550			0.20
Italy	€	3,150	3,750	2,600	0.20
Norway	Kr				0.22 (2003 – 2005)

1.3.3. Operational costs

Due to the large number of residential fires and the resulting significant losses, there is a need to allocate a significant amount of resources to fire incidents responses. Governments around the world allocate a substantial amount of their budget to funding fire services, fire protection in buildings, and fire insurance administration - an average of 0.18 per cent, 0.26 per cent, and 0.05 per cent of GDP, respectively (see Table 1-3).

Table 1-3: Economic-statistical evaluation of cost of fire, 2008 – 2010 (Association, 2014, Brunshlinsky et al., 2016)

Country	Cost in portion of GDP (%)		
	Cost of fire service	Fire protection in buildings	Fire insurance administration
Singapore	0.03	0.40	0.02
Czech Republic		0.16	
Romania	0.05 (2010)		
Slovenia	0.05 (2002 – 2004)	0.16 (2002 – 2004)	0.06 (2002 – 2008)
Denmark	0.07 (2006 – 2007)	0.26 (2005 – 2007)	0.09 (2005 – 2007)
Norway	0.11 (2003 – 2005)	0.36 (2006 – 2008)	0.10 (2003 – 2005)
Hungary	0.13 (2007 – 2008)		
Sweden	0.13	0.20	0.05
New Zealand	0.16	0.24	0.08 (2004)
Poland	0.16		
Australia	0.17	0.35 (2006)	
Finland	0.19		0.03
France		0.18 (2006 – 2008)	0.07 (2006 – 2008)
Germany			0.04 (2005 – 2007)
Portugal	0.19 (2006 – 2008)		
United Kingdom	0.20	0.23	0.10
Netherland	0.21	0.31	
Japan	0.26	0.12	0.09
Italy		0.35 (2006- 2008)	0.04
United States	0.29	0.29	0.12
Canada		0.32 (2006 – 2008)	

The Australian government has spent AUS$11,860 million per annum (2005) to meet the costs of fire including the cost of anticipation (57 per cent), cost as consequence (14 per cent) and cost in response (29 per cent) (Ashe et al., 2009). The cost of anticipation largely relates to fire-protection in buildings, fire safety measures in structures or infrastructure, fire-safe consumer items, and maintenance of fire safety equipment. Table 1-4 shows the total amount of funding spent by fire services in Australia on fire-related incidents or associated items (Ashe et al., 2009). Also, note that the volunteer fire service receives a large portion of the allocated budget (17 per cent of total), which is difficult to estimate in dollar terms.

Table 1-4: The total cost of fire in Australia, 2005 (Ashe et al., 2009)

Cost component	**Total cost ($ million)**	**% of total**
Fire in buildings	1740	14
Fire safety measures in structure/infrastructure	1850	15
Fire safety education and training	40	<1
Insurance administration	325	3
Fire safety in consumer items	1600	13
Fire research	20	<1
Maintenance of fire safety equipment and measures	1200	10
Cost in anticipation	**6775**	**57**
Cost of injury due to fire	370	3
Property losses	990	8
Loss of business	50	<1
Environmental cost	195	2
Heritage and cultural costs	50	<1
Wider economic distortions	-	<1
Cost as a consequence	**1665**	**14**
Fire service response costs	1330	11
Volunteer fire service	2000	17
Private fire service	100	<1
Criminal justice costs	-	<1
Cost in response	**3430**	**29**
Total cost of fire in Australia 2005	**11,860**	**100**

1.3.4. Policy and planning implications

Fire agencies have onerous responsibilities to perform that can mean the difference between life and death outcomes. They are not only accountable for timely response to emergency calls; they are also responsible for conducting systematic reforms to building designs and regulations, and for the development and implementation of prevention programs to improve community safety. Therefore, their responsibilities cover prevention, preparedness, response and recovery.

Assessments of risks to individuals and communities (likelihood and severity) are the key responsibility of fire service agencies; nonetheless, the major tasks remain in responding operationally to fires when they occur and extinguishing them within the response time threshold. This operational-centred view of emergency management often seeks improvement through the use of better equipment, response time optimisation and efficient use of resources.

This study contributes to several policies and planning strategies encapsulating the activities of fire services. It provides an evidence base for decisions to promote fire safety:

- The Metropolitan Fire Brigades Act (1958) outlines a legislative framework to assist fire services to face contemporary challenges. It includes a more comprehensive description of the wider role of fire services. The Act also instructs all fire authorities to promote fire safety and fire prevention in order to reduce the level of fire risk. The other policies relating to the promotion of fire risk safety are contained in the MFB Annual report (2015 – 2016). The report states that the fire services were taking initiatives for fire prevention, but that their ***risk categorization*** as a means of ensuring fire prevention was failing to take account of factors such as demographics, time of day or period in the year. The commission recommended a shift towards a prevention-focused approach, proposing that fire authorities should be given statutory responsibility to promote fire safety – to educate the public about the fire, its causes, its dangers and ways to combat it.

  The report of the Victorian Fire Services Review 'Drawing a line, building stronger services' (2015) also stresses that fire authorities should be working together to ***identify the risk profile*** and the resources that are required to meet the risk at an acceptable level. It is also intended to protect communities from risk and to prevent incidents from occurring. A better understanding of and focus on the risk profile, will mean that resources will be allocated to regions at greatest risk, thereby improving the service to the community.

- The development and implementation of localised strategies are also prominent in the Government response published in 2016 with a view to establishing a stronger emergency service. This publication suggested that three key themes should underlie fire strategies: the people and culture, working better together, and the effective management of resources. These themes can facilitate better ***local-based, decision-making*** and restore the focus on delivering better and more responsive service to the community. Arguably, a knowledge and understanding of the community and its socio-economic characteristics are likely to assist with identifying the risk profile across the region and establishing effective resource management in order to meet the risk at an acceptable level. Working together implies collaboration and cooperation with partners such as fire organizations, government, and communities to promote fire safety and to strengthen the capability of fire services.

Currently, fire and rescue services have a mandate to better understand the risk affecting different demographic groups as a means of risk reduction (rather than fire-fighting) strategies. However, effective fire strategies and policies require a different approach from this traditional one. A new paradigm shift in fire strategy and policy making, therefore, should involve a more strategic approach which recognizes the possibility of mitigating fire risk, improving community awareness and resilience and setting up priority areas for effective policy interventions.

This study addresses these policies and strategies by:

- quantifying the geographical distribution of residential fires and to examine the spatio-temporal patterns that they exhibit across Melbourne Metropolitan region;
- developing a mathematical model that examines the likelihood of residential fire risk by having insight the historical fire incidents occurred within the neighbourhood; and
- statistically exploring and examining the situated context that discriminates between areas of different residential fire risk profile.

1.4. STUDY CONTEXT

The study context for this research is the Melbourne Metropolitan region (see Figure 1-1), which is one of the most densely populated regions of Australia. Over the two decades, the region has seen major developments mainly in the heart of the city, known as The City of Melbourne, and the Melbourne Central Business District (CBD), Southbank and Carlton areas through the process of urban consolidation. According to the ABS (2016), the estimated population in the Melbourne Metropolitan region in 2016 was about 4.88 million residents and, compared with the total population in Victoria, the region accounts for around 76 per cent of residents. Melbourne West has had the largest population growth with an increase of 22,700 residents, followed by Melbourne Inner with 17,400 people and Melbourne South East with 17,200 people.

In relation to population density, Melbourne Inner has the highest population density with the largest inner-city density of about 13,000 people per km2, Carlton with 9,500 people per km2, and Fitzroy with 8,000 people per km2. This condition has led to a changing of the population centre to the suburb of Glen Iris. The rapid population growth has driven the increased demand for dwellings in the Melbourne Metropolitan region. The total number of dwellings in 2011 was about 1,572,161 units with 91 per cent occupancy. This was higher than the whole of Victoria with only 88.7 per cent of dwelling occupation, and the whole of Australia with 89.3 per cent occupancy.

The key reasons for choosing the Melbourne Metropolitan area for this study are as follows:

- Over the last two decades, the geography of Melbourne has been significantly transformed in terms of both the built-up environment and the increased cultural diversity. The restructuring of urban systems is driven by higher density developments in and around key activity centres and Transit-oriented Development (TOD) nodes to increase accessibility to public transport and public services hubs such as fire and emergency services or health care centres (Dittmar and Ohland 2012; Searle et al., 2014). This urban transformation poses new challenges for the resource management and delivery of emergency services in inner and outer suburbia;

- The density of urban use in Melbourne has increased. It has led to significant changes in the neighbourhood character, urban design, the scale of spatial interactions, local learning and sense of belonging. Consequently, the fire risk patterns in high-density areas in a compact city model might be different from those exhibited in a single-dwelling, low-density housing environment, which have not being tested using sophisticated statistical models using disaggregate fire incident data. Given these changes, it is important to understand the spatiotemporal variability of fire risk across different parts of Melbourne; and

- Melbourne has also a growing multicultural population throughout the inner suburbs and its surrounding outer and peri-urban suburbs. During the last decade or two, the region has attracted a large number of interstate migrants, making Melbourne one of the most densely populated regions in Australia. The characteristics of Melbourne have, thus, shaped various patterns and fire risk drivers. The needs and cost of managing fire have increased, necessitating a new approach to fire management in order to optimise resources and mitigate the level of fire risk within the region. The mapping of geographical variability might help to identify areas with a high fire risk level. It can then be used to target these areas more efficiently, thereby making more effective use of fire prevention and intervention initiatives. Moreover, the strategy used to improve the effectiveness of education programs and awareness campaign on emergency management should be appropriate for the targeted group.

Therefore, the Melbourne Metropolitan region is an appropriate one for examining the residential fire pattern and its drivers.

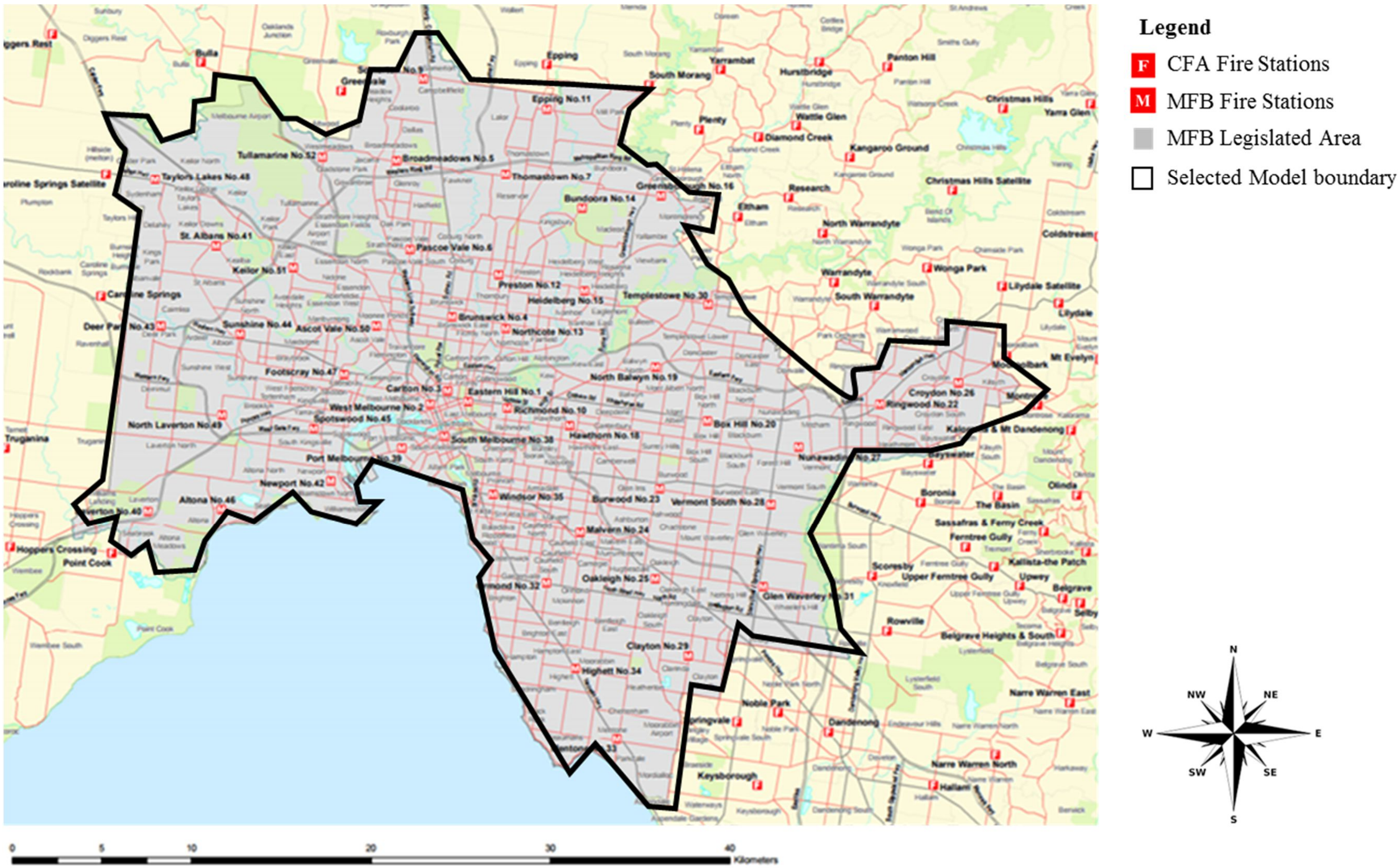


Figure 1-1: Study area of the Melbourne Metropolitan region with the MFB Boundary

1.5. THESIS STRUCTURE

This thesis comprises seven chapters, which are structured to address the main aim and associated research questions. This chapter introduced the topic, set out the objective and research questions, briefly explained the rationale, highlighted the research problems and outlined the thesis structure.

Chapter 2 provides an overview of the literature relevant to urban residential fire risk. The definition and drivers of fire risk are discussed in this chapter. The chapter also provides an in-depth understanding of the concept of residential fire risk in the context of space, time-specific, and situated context from the perspective of propagation of risk information. Moreover, this chapter develops a modelling framework for residential fire risk in terms of linking space, time, and situated context with fire risk.

Chapter 3 presents a comprehensive review of the various approaches, methods and techniques used for measuring residential fire risk. It reviews spatial indicators which influence the likelihood of fire occurrence. The advantages/disadvantages of modelling techniques are examined with justification of adopting the Markov Chain approach with spatial statistics. The research gaps are also discussed in this chapter.

Chapter 4 presents the research methodology, beginning with a description of the research design, methods, and modelling techniques. This is followed by an examination of the research data which consists of an aggregate dataset and a disaggregate dataset, and the collection and justification of data. The related models (e.g. Markov chain and Geographically Weighted Regression) are presented.

Chapter 5 presents the results of fire risk modelling. The chapter begins with a summary of data acquired from the descriptive statistics including temporal patterns and spatial variability in fire incidents. It reports on residential fire occurrence in the Melbourne region. The chapter discusses the Markov chain, which was applied to examine the likelihood of residential fire occurrence. This chapter answers the first two research questions: *How does a residential fire pattern occur over time and space*? and *Can the probability of a residential fire occurrence be predicted as a stochastic process*?

Chapter 6 discusses the Geographically Weighted Regression model, which was used to examine the relationship between fire risk and residential variables over space in terms of risk variability. Geographically Weighted Regression was formulated to log the probability of fire occurrence as a dependent variable and five major residential indicators as independent variables. The results, overall, indicated that residential fire risk is likely to be related to local spatial interaction. This chapter focuses on answering the third research question: *How do urban characteristics impact on residential fire risk*?

In Chapter 7, the aim and research objectives are reviewed and discussed, and conclusions are drawn. The chapter also summarises the key findings of this study and discusses the potential contribution of this study. It presents key strategies and recommendations based on the main findings of the study. This chapter focuses on answering the fourth research question: *What spatially-integrated strategies can be developed to mitigate fire risk in an urban setting*? Finally, the limitations of the research and the avenues that it offers for future research are discussed in this chapter. Figure 1-2 summarises the chapters of this thesis.

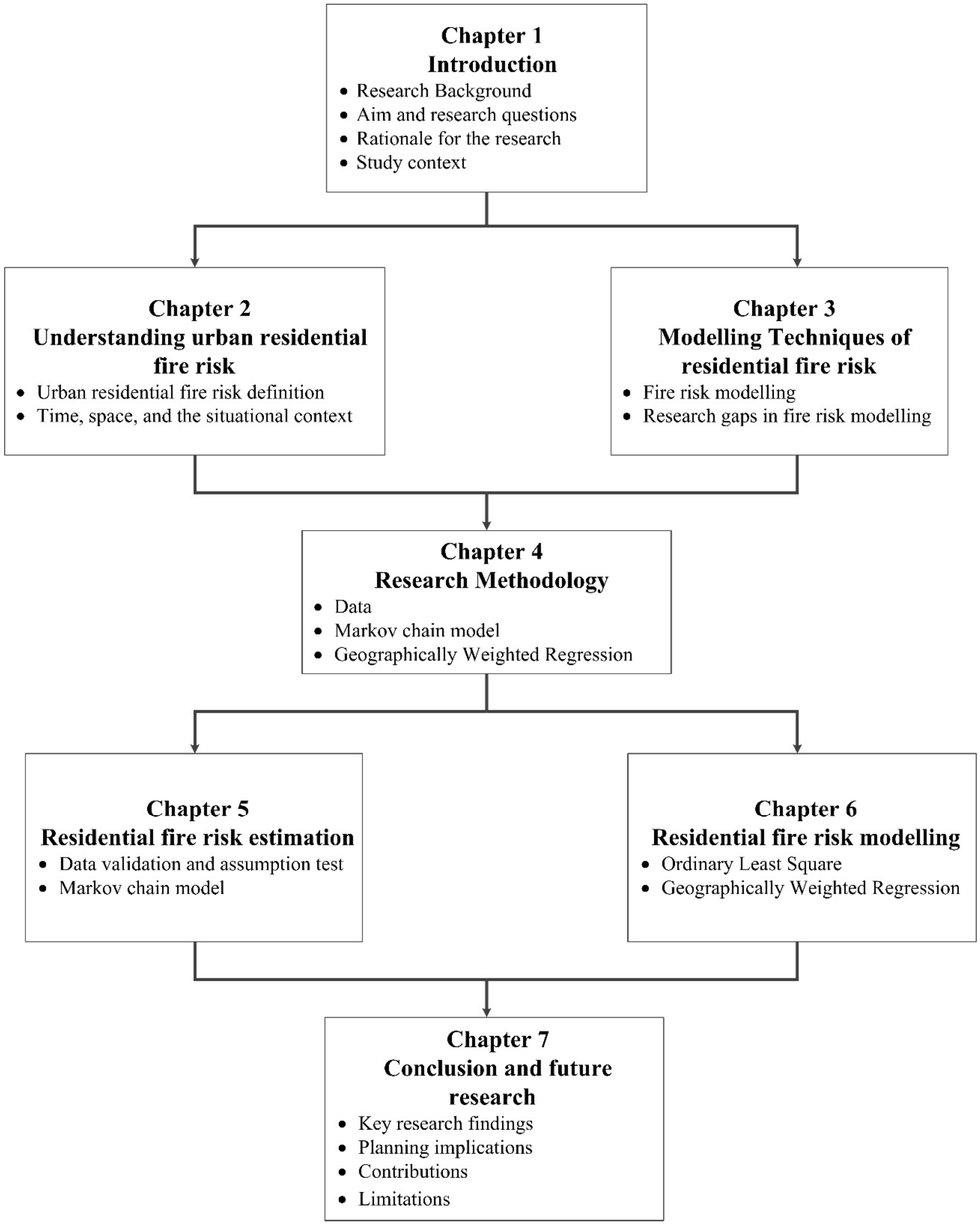


Figure 1-2: Thesis structure

1.6. SUMMARY

This chapter has established the research context by stating the aim and four interrelated research questions. It provided the rationale for undertaking this research by arguing the importance of examining residential fire risk using more sophisticated models. This research is important as it models the residential fire risk, thereby providing a more accurate and robust means of investigating the spatial pattern of residential fire risk at the local level. This would help fire agencies and emergency planners to improve their understanding of fire risk and its associated factors in order to help reduce the fire risk levels. Moreover, this research may assist the Metropolitan Fire Brigade to develop area-specific strategies for reducing fire risk by means of reliable models to improve the efficiency of fire safety campaigns and education programs at both the local and global levels. The proposed novel mathematical modelling approaches seamlessly and simultaneously increase the accuracy and robustness of residential fire risk calculation and capture in more detail the effect of spatial characteristics on fire risk.

The next chapter presents the literature review and develop a theoretical framework for modelling fire risk in the frame of space, time and situated context.

CHAPTER 2
URBAN RESIDENTIAL FIRE RISK

2.1. INTRODUCTION

This chapter discusses the concept of residential fire risk and explores its various drivers by reviewing fire risk in term of space, time, and situated context. It provides an overview of residential fire risk, local learning, memory effect, and socio-spatial barriers to the propagation of risk information.

The chapter consists of five sections. Section 2.2 presents various definitions of residential fire risk. Section 2.3 describes the spatial-temporal of residential fire risk pattern. The conceptualization of fire risk drivers in term of space, time, and situated context is explained in section 2.4. Section 2.5 summaries and concludes this chapter.

2.2. FIRE RISK

2.2.1. Definition of fire risk

Fire refers to a phenomenon where emission of heat and either smoke or flare occurs and subsequently requires one or both mechanical and human intervention for its control (Williams, 1982). Specifically, urban fire refers to the fire that occurs in an urban area. There are several types of urban fires. Firstly, bushfires are those which may destroy trees in woods or forests, bush and grass, or plantation or nursery stock. Structure fires involve the inside of buildings or structures including houses, sheds, shops, and offices. Finally, non-structure fires are those fires occurring outside of a structure, in places such as storage yards, and vehicles (CFA, 2012).

Corcoran et al. (2011b) took a different perspective in classifying urban fires. They offered five categories namely residential fires which include all fires involving residential property, followed by secondary fires that pertain to all fires involving derelict buildings or vehicles, refuse containers and outdoor structures such as a fence, gate, and road sign. The third category is vehicle fires which include the burning of mechanical or motorised modes of transportation, followed by malicious false alarms where fire is reported in the knowledge that it actually not occurring, and lastly, suspicious fires for suspected arson. This study focused on urban residential fire in an urban area as a structure fire involving residential properties only in the urban area.

As many studies have shown, fire risk is not clearly defined but has been quantitatively measured by, for example, the count of fire incidents (Corcoran et al., 2011a, Duncanson et al., 2002) and fire rate (Chhetri et al., 2010, Corcoran et al., 2013, Špatenková and Virrantaus, 2013). There are various theoretical frameworks and definitions of residential fire risk derived from different perspectives. However, those definitions are similar in that they view fire risk as a probability. For example, Špatenková and Virrantaus (2013) defined fire risk as:

> '… a risk, which combines both probability of the incident and its consequences' (Špatenková and Virrantaus, 2013, p. 49)

In the field of fire safety engineering, the definition of fire risk is:

> 'The product of the probability of fire occurrence and the expected consequence or extent of damage to be expected on the occurrence of fire' (Xin and Huang, 2013, p. 73)

In another study, the term 'fire risk' is also defined as a probability:

> 'the probability of fire starting determined by the presence and activities of causative agencies' (Chuvieco et al., 2010, p. 47)

In summary, in each of these definitions, the commonly occurring and essential elements of the fire risk are the fire itself, the expectancy of fire occurrence (i.e. the probability, density, and rate of fire), and the consequences of fire (i.e. damage, financial loss). The nature of fire is complex as each occurrence has a unique combination of the elements above; therefore, in this thesis, fire risk is narrowly defined as follows:

'Fire risk is the probability that a fire will occur.'

Although this is a narrower definition, it still enables a more comprehensive discussion of the aforementioned elements. Defining fire risk as only the probability of fire occurrence may be a convenient approach, without ignoring the array of abovementioned essential elements pertaining to fire risk (i.e. the consequences).

2.2.2. Spatial-temporal pattern of residential fire risk

A substantial body of research demonstrates evidence that residential fires have spatial-temporal dependence, meaning that such occurrences are spatially, temporally, and spatial-temporally correlated. In the following sections, a discussion of fire risk patterns is presented.

2.2.2.1. Temporal patterns

Temporal patterns are commonly used to identify and analyse the distribution of fire occurrence over time. They indicate whether a sequence of fire occurrence during certain period show a trend or seasonal pattern. There are four major patterns: trend, cycle, seasonal pattern, and trend with seasonal pattern (see Figure 2-1). It is to be noted that the distribution of fire occurrence is not random; instead, fires tend to occur at specific and predictable times. The causes and origins of residential fires influence their temporal pattern.

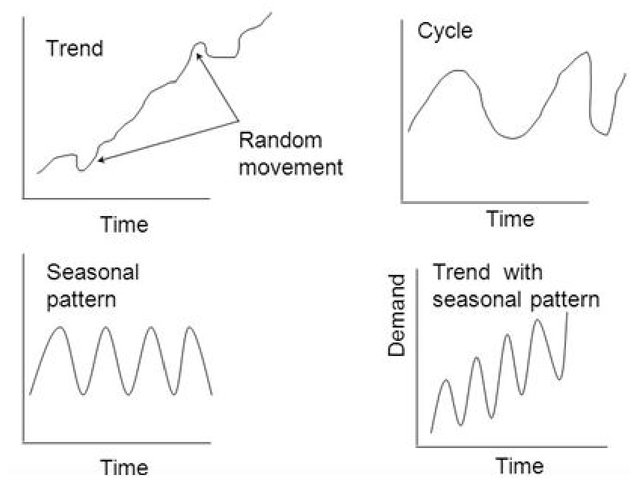


Figure 2-1: Illustration of temporal pattern (Box and Jenkins, 1970)

Numerous studies have demonstrated that residential fire occurrences have a seasonal pattern in terms of month of the year, day of the week, or time of the day. Asgary et al. (2010), for instance, found that residential fires caused by arson mostly occur at night between 7:00 pm and 4:00 am. During this period, the many vacant buildings and the darkness provide an increased opportunity for people to engage in criminal activities and set structures on fire. Moreover, residential fires caused by children tend to occur between 3:00 pm and 8:00 pm. During this period, children are mostly at home and are often unsupervised. Also, it has been found that residential fires caused by electrical failures occur more frequently during the late afternoon and early morning. The reason why evening fires occur is due to residents' lack of vigilance activities at home such as cooking, and issues related to the usage of electricity.

In regard to fire occurrence over time, the Australasian Fire and Emergency Service Authorities Council (AFAC) found a similar pattern. Residential fires occur mostly between 5:00 pm and 9:00 pm (AFAC, 2009). The rate also increases during that period with 40.6 per cent of fires originating in the kitchen and 21.9 per cent in the bedroom. They also noted that most fires occur due to appliances or equipment being left unattended (24 percent), residents falling asleep (8.6 percent), abandoned or discarded materials (4.1 percent) and electrical failure (4 percent). A similar pattern is seen in New Zealand where residential fires occur between 4:00 pm and 9:00 pm when people are mostly at home, and cooking activities are a major cause of residential fires. However, in the US, residential fires occur between midnight and 6:00 am, with the most considerable number occurring between 1:00 am and 2:00 am, while non-fatal residential fires occur between 5:00 pm and 9:00 pm (USFA, 2014). A reasonable explanation is that people are usually asleep at midnight, which increases their vulnerability. In the instance where there is no smoke alarm, fatalities may occur due to the failure of residents to awaken up during the fire. Meanwhile, non-fatal residential fires occur because of daily household activities such as cooking which is usually done during the late afternoon and evening (Jennings, 2013).

Furthermore, the occurrences of residential fires also vary according to the day of the week, which presumably indicates the causes. For instance, the weekend is a critical time for residential fires caused by arson and vandalism due to weekend-related activities when drug and alcohol consumption increases as do the number of unsupervised properties. Meanwhile, residential fires caused by children occur most often during weekdays due to children being at home alone because their parents are working (Asgary et al., 2010). Concurring with other research, Corcoran et al. (2011b) pointed out that the relative risk of residential fires in Australia is greater during a long weekend. The number of residential fires, at 2,963 fires per day, increases during long weekends. This tendency is slightly higher than the fire rate in normal situations which is 2,817 fires per day.

There has also been documentation of monthly and seasonal trends. For instance, numerous studies found that winter and other cold weather conditions are critical periods for residential fire incidents and have the highest rate of fires per day (Corcoran et al., 2011b). Some areas have the highest number of residential fire incidents in the spring when people have a greater opportunity to remain outside longer. School holidays also contribute to an increase in fire occurrence (Corcoran et al., 2011b). Regarding fire-related injuries, the AFAC (2009) pointed out that the rate of residential fire injuries increases slightly during the colder months from June to August and drops during February and March. In New Zealand, a similar temporal pattern is evident; the peak season for residential fires is from July to August during winter. However, the rate of fire-related injuries decreases in November. A similar pattern is observale in the US where the number of residential fires, especially fatal residential fires, is much higher in the winter season which peaks in January.

Overall, this clearly shows that, over time, there is a unique pattern of the distribution of fire risk. The patterns have a correlation with the causes and their origin, and thus are attributed to human behaviour and activities at certain time.

2.2.2.2. Spatial patterns

One way of identifying and analysing the distribution of fire occurrence over space is to measure spatial patterns. A spatial pattern is, in general, defined as a perceptible structure, placement, or arrangement of objects over space. A pattern may be discerned in the arrangement if points which may be clustered or in a line. In the case of fire occurrence, a spatial pattern indicates whether fire occurrence is clustered or dispersed over space. Figure 2-2 illustrates spatial patterns over geographical space. There are four major patterns, namely random, clustered, homogeneous-isotropic, and homogeneous-anisotropic. A random distribution does not imply any constraint regarding the position of fire occurrence. The position of fire incidents is mutually independent (Figure 2-2A). Clustering pattern indicates constraint on the position of fire occurrences. The pattern displays clearer and denser clusters than in a random distribution (Figure 2-2B). Homogenous implies that the location of a new fire occurrence is dependent on its distance from the position of a fire occurrence in the past. A homogenous pattern can be isotropic or anisotropic (Figure 2-2C, D). An anisotropic pattern has angular preferential position of points with specific spatial ordering points (Genier and Epard, 2007). In the case of fire occurrence, a homogeneous distribution has never occurred.

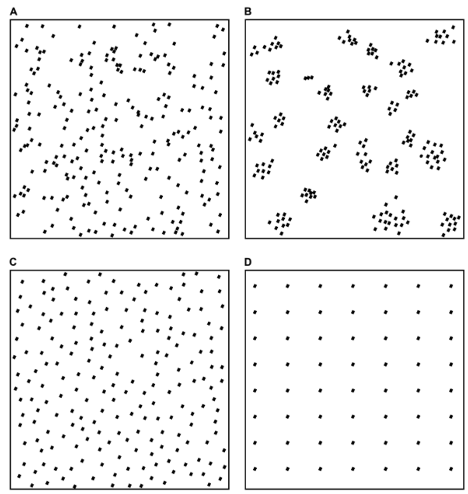


Figure 2-2: Illustrations of spatial patterns: A. random, B. clustered, C. homogeneous and isotropic, D. homogeneous and anisotropic (Genier and Epard, 2007)

Spatial analysis enables the spatial pattern of fire occurrences to be quantified and attributed to spatial characteristics of such areas or regions. Many seminal studies on residential fires (Ceyhan et al., 2013, Chhetri et al., 2010, Jones et al., 2013, Wuschke et al., 2013) explicitly explored the spatial pattern of residential fire for geographical characteristics to examine the correlation between various spatial indicators of residential fire occurrence. Furthermore, a range of geographical indicators has repeatedly been found to relate to the distribution of residential fire occurrence. Specific geographic characteristics are associated with high residential fire densities while others remain at a relatively low rate. For example, areas of high population density are likely to have the highest fire intensity and number of buildings downtown as well as along major streets, which potentially increases the probability of fire incidents. Areas with high-density dwellings are likely to have high residential fire density than low-density areas (Ceyhan et al., 2013). In areas such as the Central Bussiness District (CBD) or th einner suburbs with high-density buildings, fire risk is likely to be higher than in other areas (Leth et al., 1998, Jones et al., 2013, Sufianto and Green, 2012, Yen and Chen, 2004). Residential fire incidents are further clustered according to the built environment and the socio-economic demography. This variation in the built environments may indicate the social and economic characteristics of the areas. Hence, there are specific areas of a city that, more than other areas, are vulnerable to residential fires.

Other examples include areas with the newest residential structures that might not be as vulnerable as areas with older structures, although a high population density is prevalent in the former. These structures may be designed and built with fire-resistive features such as smoke alarms and extinguishing systems installed during construction. Conversely, older dwellings may be prone to faulty electrical circuitry or heating or other hazards due to age and lack of maintenance. Wong and Lau (2007b), for instance, showed that old buildings, especially older apartment buildings, usually pose a potential fire risk due to lack of fire-safety installations. In fact, these areas represent a clustering of similar socioeconomic characteristics. Low-income persons often live in older structures which typically lack in fire detection devices such as smoke alarms and sprinkler systems.

In summary, this clearly shows that fire risk is not uniform across space. Different socioeconomic and structural attributes that constitute the building block of a space indirectly influence the probability of fire occurrence. This spatial pattern reveals that not all people are equally vulnerable to fires. Fire risk depends on the spatial variability of urban space where some areas are more vulnerable than others due to local spatial characteristics.

2.2.2.3. Spatial-temporal patterns

Spatial-temporal patterns are used to analyse the distribution of fire occurrence across space and over time. They indicate whether spatial patterns of fire move or transform over time. Figure 2-3 illustrates the pattern transformation across space and over time. It is possible to have the same spatial patterns during certain period as well as having a trend or seasonal spatial pattern.

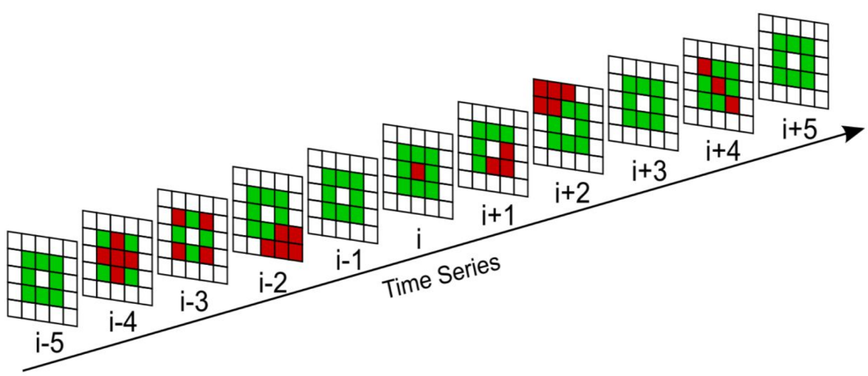


Figure 2-3: Illustration of spatial-temporal pattern (de Oliveira and Renno, 2014)

The dynamics of residential fire risk may vary; it may pertain exclusively to either time or space alone or co-occurring in both dimensions. For instance, a study by Asgary et al. (2010) examined spatial and temporal dimension of a residential fire in Toronto, Canada. By mean of GIS, they conducted a mapping of residential fire intensity by the time of day and month of the year. They further found clear patterns in the simultaneous interplay of time and space that varied according to the type of fire which depends on the cause, such as arson and children playing. The finding demonstrates that fire occurs when specific condition and situation meet simultaneously. Fires are more likely to occur where unsupervised children are playing at home (i.e. afternoon), for instance.

Wuschke et al. (2013) examined the temporal and spatial dimensions of fires in the criminological environment through the lens of crime pattern theory and routine theory. They emphasise that there exists an environmental trigger that influences fire occurrence. For instance, the patterns of urban residential fire occurrence may be affected by criminal events such as arson-fires and vandalism-related fires. These crimes occur because of less surveillance, or a lack of lighting around vacant buildings, which provides more significant opportunity for the perpetrators of residential fires. They found that residential fires and burglaries occur in the same place but at different times. The study successfully bridges the divide between investigations on the time and place of fire occurrence. Several other studies, namely the one conducted by Corcoran et al. (2016), employed a similar approach when examining the interplay between the spatial and temporal dimension of fire occurrence.

Those studies, therefore, suggest that residential fire risk is temporally and spatially dependent. They stress the understanding of the relationship between environment and human behaviour to provide context to the spatial and temporal distribution of fire occurrence. This relationship indicates the likeliness of residential fires to occur when people are at home and preparing meals, and fire resulting from heater faults are more likely to occur in Winter.

2.3. RESIDENTIAL FIRE RISK DRIVERS

Understanding residential fire risk is a complex task. According to Clarke et al. (2015, p. 1114) ‘Risk is not understood in rational, predetermined ways, nor experienced in the same way by all people, in all contexts. Rather it is subjective and contextually constructed and determined’. This statement raises an important question of what drives fire when different contexts are taken into consideration. Reflected by the body of literature that has been discussed thus far in this chapter, it is reasonable to call for a further examination of the correlation between drivers and context; given that the perspective of spatial relation, time specificity, and the situated context of residential fire risk as well as people’s behaviour during a fire and how their behaviour affects risk, have been the subject of many studies.

2.3.1. Space and 'local learning'

There are many interpretations of the term 'space' as it is contextual and used by scholars of various disciplines. Space is the boundless, continuous expanse in which objects and events are contained and have relative position and direction (Yuan, 2004). In practical terms, space can be constructed as a physical entity present at different geographic scales or as a constructed entity (Pries, 2005). Space is also often interpreted as particular geographical units such as villages or cities (Kellerman, 1989). Those definitions clearly suggest that there are two elements in the construction of space: individual space and societal space.

Kellerman (1989) classified individual space into three levels: (i) Micro-space—the smallest individual space. It is likely equivalent to the bubble surrounding an individual; (ii) Meso-space which includes the home and neighbourhood; and (iii) Macro-space which refers to areas beyond the home or neighbourhood where social interactions by the individual still take place. In the same study, Kellerman (1989) defined societal space as that which is has a boundary within which the spatial interaction among members of the local community takes place. Similarly, Sorge (1999) pointed out that societal space is a space that is bounded by the analytical characteristics of society and is internally structured into subspaces and institutional domain. From these concepts of space, it is clearly evident that space is not only defined as a physical area that is often regarded in terms of its three linear dimensions (i.e. longitude, latitude, and depth), but delineates the boundary which shapes the interactions within a community.

In expanding the concept of space as a societal space, Simonsen (1996) conceptualises space in three different ways: (i) space as a material environment where space provides the arena for social interactions; (ii) space as a differentiation which denotes that different places, regions or localities are substantially dissimilar; and (iii) space as a social spatiality. Simonsen's concept stressed the significance of social processes that underpin 'what' occurs in a place. Moreover, the formation of such occurrence, or the 'how,' is determined mainly by spatial relations that influence the processes and the nature of the social interaction. Consequently, the concept places space as one of the dimensions of social practice (Raper, 2000). In other words, spaces are socially constructed. They are created, constructed and represented by spatial practices and relations (Lefebvre, 1991). This clearly shows that space is related to spatial individuals' network. Space thus has the function of connecting an individual with his/her surrounding neighbourhood. People often form a localised network within a geographic space to share information and exchange ideas, knowledge and experiences.

In regard to the concept of space from a social perspective, this thesis argues that space relation plays an important role in spatial interaction or the ways through which information about fire risk is communicated within a neighbourhood. It is therefore necessary to understand the way that individuals within a neighbourhood learn from their network. Learning, in general, is the act of acquiring new knowledge, or adjusting and strengthening existing knowledge, behaviour, or other values and may involve synthesising different types of information. Kolb (1984) defined learning as '…the process whereby knowledge is created through the transformation of experience'. However, some studies (Reed et al., 2010, Wenger, 1998) pointed out that learning is not only the process of acquiring new information and knowledge but is an outcome of spatial interaction with others. Wenger (1998), for instance, stated that learning is a social interaction practiced in a community. Reed et al. (2010) stressed that learning in social theories refers to a process of social transformation in which individuals learn from each other in a way that can benefit wider social systems. According to these standpoints, individuals use their space as an arena to acquire new knowledge or skill, understanding, and reinterpreting knowledge, and they learn at their localised network.

Reed et al. (2010) also analysed how spatial interaction among members of a society influences their views and perceptions. They concluded that the interaction between individuals within a circle of acquaintances within a geographic milieu plays a vital role in directing and diffusing information. O'Brien et al. (2010) also pointed out that, in the context of disaster management, the views and perceptions do not refer to the spatial distribution but the interconnectedness of individuals in the networks. Distancing an individual from the network lessens the effectiveness of risk management. Originating from the concept of local learning, this second school of thought is informed by the model of distance decay law where distance and interaction are inversely proportional. The shorter the distance, the more likely that interaction will occur; the further the distance, the less likely that interaction occurs. Literature suggests that the enhanced spatial interaction may lead to quicker and more successful diffusion of information because individuals within a local network know one another and are in frequent contact or interaction within their network. It is therefore important to understand not only the concept of space and related spatial interactions, but also how space forms the perception of information, especially the perception of fire risk that an individual or community acquire from others within their local network.

As a synthesis of these theoretical perspectives, space potentially shapes the communication of fire risk to individuals or communities. Clark et al. (2015) highlighted that fire risk is part of the spatial network. Individuals who have had past fire experience, either directly or indirectly within or received information about fire risk from their neighbourhood can amplify or reduce risk perception. Additionally, the generation of risk information at the local level can prompt individuals to pay more attention to fire risk in the future (Clark et al., 2015). Although in a different context of fire risk, Clode (2010) also found that individuals who have had experience of or have heard about a residential fire incident within the vicinity of their home become more aware of risk, which in turn helps them prepare for or prevent the threat of potential fire hazards. According to this, there is a correlation between distance of the original source of information and how individuals learn and response to the information by taking any action to reduce fire risk.

2.3.2. Time and 'memory effect'

Space is relatively easy to conceptualise, while the notion of time presents some challenges (Peuquet, 1994). There are a number of definitions of time. Time, in general, is a component quality of various measurements used to sequence events and to compare the duration of events or the intervals between events. Peuquet (1994) adopted a definition that refers to an individual time. She suggests that time is an individual observation of the changes occurring in objects in space, be it in the form of transformation or movement. This definition, consequently, is open to various interpretations.

Expanding on this definition, Peuquet (2002) stated that time may take on different meanings for different individuals. It can be represented as an experience, a major dimension, an ordering framework, or an event of biological significance. Experiential time refers to personalised images of time as being short or long, passing quickly or slowly. Time as a significant dimension refers to a measure along which all events occur, and around which human activities evolve. Time as an ordering framework applies to which event precedes or follows another and the following chains of events or developments. The calendar and the clock are two primary tools in the organisation of daily, weekly, monthly and annual flows of events. They are tools used to indicate biological time, which regulate organisms and activities.

Unlike the concept of space, the notion of time in society has not been treated and developed systematically either by geography or by sociology. Although social time has been the focus of several sociological works employing different perspectives, the approaches used lacked a clear, detailed distinction between the time of individuals and the time of societies. Kellerman (1989), however, highlighted a significant difference between individual time and societal time which is the finitude of individual time, compared to the relative infinitude of societal time. Duration, thus, has different meanings in these two times. However, the definition of time in this study does not distinguish between individual time and societal time.

The meaning of time has especially been developed with regard to the context of time and space, and thus there has been an expansion of the definition of time (Dainton, 2014). Time no longer stands as a separate single dimension as it is seen as integral to space. Hagerstrand (1965) introduced the concept of time geography. It is a theory of behaviour geography that explains the way that an individual move in time and space. He noted that 'time has a critical importance when it comes to fitting people and things together for functioning a socioeconomic systems' (Corbett, 2001). So even an individual residing at a point that is near a certain location, may not be able to allocate enough time to travel to that particular location. Spatial proximity alone does not make an inherent difference.

Time geography has become the key element of the diffusion process. Hagerstrand (1968) explained the role of time in the diffusion process. Time is treated as an interval of time, measured as the period from the initial diffusion to its acceptance or rejection. Concurring with this, Rogers (2003) also pointed out that time can exist between the transmitter and receiver of messages in the process of information propagation. This suggests that time plays an important role not only in the diffusion process but also in the retention of information.

Any efforts to accept, store and process information are referred to as 'retention of information'. It is therefore necessary to understand the meaning of information retention. Matlin (2013) offered a definition that explains it as a process of maintaining or memorising information over time. She also pointed out that it is related to the ability to encode, store, retain, and subsequently recall information and past experiences. In support of this, Ma (2015) used a similar term to define retention of information as the process of information transmission over time.

Information retention is affected by the several crucial factors. First, individuals are more likely to retain the information if it is specific, consistent, definite and repeatedly transmitted. The probability of maintaining long term memory is higher for individuals where events that negatively impact on them such as fatalities, are involved. Second, the individual is likely to store fresh or updated information. Individuals can temporally hold information originating from a wide range of perspectives in the distant past through the immediate past (Dainton, 2011). However, one may have a small memory capacity reserved only for the immediate past or current event (Holman and Silver, 1998). Yung (2008) also indicated that recent past information, therefore, may still apply, but long-time past information may not apply because of the changes over time or due to it no longer being relevant. For example, the information about a fire that has occurred in the immediate past is possibly still relevant. Potentially, it prompts individuals to be more aware of a similar incident.

This study argues that time is involved in the shaping of fire risk perception. However, there is little understanding of how experiencing or witnessing a fire incident influences the perception of future fire risk (Clark et al., 2015). Fire risk perception is temporal. The time element starts from when an individual first receives the information about risk, to perceiving or processing a decision to accept or reject, and through to implementing or confirming a decision. Hence, it is related to the time lag between fire incident and post-fire incident. Individuals are likely to have time to recover from the events (Keane et al., 2002). They are still highly distressed after the fire and remember the occurrence. This phenomenon is often referred to as the 'memory effect'.

2.3.3. The situated context

2.3.3.1. Socio-spatial barriers of a propagation of risk information

The variability in fire risk is not only space-driven and time-dependent but is also context-specific. The perception of fire risk is influenced by the situated context that differentiates one neighbourhood from others. The situated context provides the arena for local interactions that shape the information diffusion and perception of fire risk. Factors such as socioeconomic status, length of residency, and home ownership, might facilitate local interactions among residents, while others such as a language barrier prevent information sharing and risk awareness. The effective diffusion of information about fire risk requires a more targeted strategy to reach out to communities at a higher risk of fire (Rhodes and Reinholtd, 1998). A new perspective on modelling fire risk needs to consider space and time dependency and the situated context within which a fire occurs.

As discussed earlier, diffusion of risk information plays a vital role in forming fire risk perception (Clark et al., 2015, Clode, 2010, O'Brien et al., 2010). Diffusion of risk information is related to an exchange or transmission of information among individuals, groups and institutions about the existence, nature, form, severity, or acceptability of risk (Plough and Krimsky, 1987). It is arguable that the successful propagation of risk information depends on the ability of the individual or a community to create spatial interactions and relationships. Usually, better communication or interaction may lead to quicker diffusion of information over space (Rebecca, 2015, Rogers, 2003). However, measuring the way in which an individual or community interact is problematic because, arguably, the interaction is shaped by socio-structure characteristics including the social and physical environments. With this in mind, those features can serve as a proxy to measure the ability of individual or community in communicating, exchanging and sharing information. Numerous studies have described the various spatial characteristics of society that shape the communication process between individuals or among communities.

For example, Meischke et al. (2010) found that language is a most critical factor affecting the spatial interaction process. Communication becomes difficult in situations where people do not understand each other's language. Consequently, it makes the spatial interaction ineffective and prevents the message from being conveyed. In English-speaking countries, limited English proficiency is likely to be a barrier to interpersonal interaction. Similarly, Westenberg and Rutten (2017) argued that language is an essential instrument through which communication and interaction with others take place. They also emphasise the relationship between the language and proximity (i.e. nearness in place, time, order, occurrence, or relation) of individuals. Based on his ethnographic work, Williams (2012) found that language is used to construct the interaction within a neighbourhood. He demonstrated that some individuals or groups with different backgrounds in multi-ethnic and multilingual neighbourhoods try to learn the local language in their pursuit of communication and interaction with members of the neighbourhood. Others prefer to use global language (i.e. national language) for inter-ethnic communication or to engage with others. Those studies clearly show that language is an obstacle not only to creating an interaction between individuals but also to communication or exchange of information within community.

Socioeconomic status is a relevant determinant of spatial interaction. Education (Fischer, 1982), income level (Dekker and Bolt, 2005) and employment (Dekker and Bolt, 2005) are some indicators of socioeconomic status that determine the way that people interact within their neighbourhoods. Educated people are, to some extent, correlated to high-income groups and both are likely to have a positive effect on spatial networking (Dekker and Bolt, 2005, Fischer, 1982). Those groups have an extensive network, and the geographical range of their relationships is broader than the less educated and low-income groups. Affluent people are less constrained by communication means and costs and can afford to go out and communicate more often. Conversely, low-income residents are more dependent on their neighbourhood for their spatial interaction (Dekker and Bolt, 2005, Fischer, 1982). Therefore, low-income groups tend to have fewer acquaintances, but a more significant number of relatives and friends in the neighbourhood (Chatman and Pendleton, 1995, Dekker and Bolt, 2005, Kasarda and Janowitz, 1974).

Closely related to socioeconomic status is home ownership. Homeowners have more spatial interaction with the neighbourhood than renters (DiPasquale and Glaeser, 1999). The phenomenon can be explained by the tendency of homeowners to remain in a particular neighbourhood longer than tenants. In evaluating the influence of socioeconomic status on spatial relationships, other variables also have to be taken into account, notably dwelling type (i.e. separate houses, semi-detached, and two-storey houses). Helleringer and Kohler (2005) argued that usually it is difficult to disseminate information among residents living in an apartment because these residents tend to have less spatial interaction than those living in a single-storey house. Interestingly, individuals residing in houses with two-storeys or more are less likely to know their neighbours than those in separate houses.

Length of residence is to some extent related to home ownership. Home owners have better opportunity to establish a local network (Brisson and Usher, 2007). Pearson et al. (2012) found that frequent moves might break or stretch any ties between members of society and reduce communication. Conversely, a longer term of residence is not only related to a greater number of known neighbours, but also increases the opportunity to initiate spatial interaction and subsequently enhance the quality of spatial relations. It may increase informal communication among neighbours.

2.3.3.2. Spatial drivers of residential fire risk

The aforementioned drivers (i.e. socioeconomic demographic, education, dwelling characteristics) determine and are linked to residential fire risk. For instance, research by the US Fire Administration demonstrated that residential fires are more common in low socioeconomic households (USFA, 2014). Financially, disadvantaged persons are at increased risk because they are less able to invest in fire safety items such as smoke detectors, safe heating appliances and perhaps furniture that is more resistant to ignition (Jennings, 2013). However, in many cases, the fire risk for people with low socioeconomic status is related to adverse habits or lifestyles which may ignite fire such as smoking, drugs, and others (Jennings, 2013). The association between residential fires and household characteristics was also identified by AFAC (2009). The study found that a household whose members engage in drinking alcohol and/or smoking are at greater risk of residential fire.

DiGiuseppe et al. (2000) analysed the relationship between fire risk and socioeconomic characteristics and found that those who live in more disadvantaged areas are likely to be at higher risk of fire. Duncanson et al. (2002) indicated that socioeconomic deprivation may lead to greater risk of residential fires in New Zealand. Residential fires increase significantly when social disadvantage is more prevalent. Disadvantage factors that contribute to an increased risk of fire include poor education, overcrowding, poverty and unemployment. Conversely, the study indicates that formal education and adequate income are the drivers that decrease residential fire risk. Similarly, other studies such as USFA (2014) showed that lower educational level is an important factor as it correlates with increased risk of fire injury and fatalities. In Australia, those with low socioeconomic status experience a higher incidence of residential fire. AFAC (2009) found that of the most fires that occurred in Australia, in particular in Victoria during the period from 1998 to 2005, were over-represented in disadvantaged areas.

Conversely, there are also several socio-demographic factors that may reduce hazards in urban areas. For instance, in most cases, those living in cities have higher incomes and better education (Chhetri et al., 2013). High incomes may reduce the level of vulnerability since people can afford better-constructed homes and fire-safety installations such as sprinklers and smoke alarms (AFAC, 2009, Jennings, 2013). Moreover, because most decision-makers and media are in urban areas, it is more likely that people give more attention to such areas. Thus, more budget and resources to reduce risk and hazards are allocated as a priority.

Dwelling characteristics such as type and structure are also likely to be related to fire risk. The dwelling type in which fires occur differs in different countries. For instance, in the UK during the period from 1996 to 2000, nearly half of all fires occurred in flats, and only a relative few happened in detached houses (Holborn et al., 2003). Leth et al. (1998) also showed that more than 90 percent of fires took place in apartments. Conversely, in the US during 2005, most residential fires occurred in one and two-storey homes. Only 14% of fires occurred in apartments (USFA, 2014). Similarly, in New Zealand, the majority of residential fires occurred in separate houses throughout 1991–1998 (Duncanson et al., 2002). Only a few fires occurred in flats or apartments. In line with the US and New Zealand statistics, most of the residential fires in Australia occurred in separate houses with less than 6% occurring in apartments (AFAC, 2009). The percentage of fires occurring within certain housing types may differ depending on the proportion of the population living in certain residences.

Conversely, Sufianto and Green (2012) and Jones et al. (2013) demonstrated that high-density buildings such as apartments or duplexes accounted for a large number of fire incidents in dwellings. Sufianto and Green (2012) found that the main reason for the increased fire risk in high-density buildings, especially in Indonesia, is related to the lack of building regulations especially regarding the installation of fire protection equipment. About 102 of 583 high rise buildings had insufficient fire extinguishers and more than a quarter of the buildings did not have emergency exits. Sufianto and Green (2012) also argued that the behaviour and socio-economic status of most residents living in high-density buildings have the potential to contribute significantly to the increased fire risk.

Regarding type of dwelling, home ownership to some extent is likely to influence fire risk. Duncanson et al. (2002) indicated that home ownership might decrease residential fire risk. Similarly, according to a study conducted by Corcoran et al. (2007), owner occupancy is one of the primary factors used in examining residential fire risk. The study demonstrated that housing ownership decreases residential fire risk. A critical point associated with dwelling ownership is the residential mobility. The Australian Bureau of Statistics recorded that over half of the people living in apartments have frequently moved in the last five years from one building to other buildings, from an area to other areas that are either similar or different (inside or outside inner suburbs). In contrast, people living in houses report that they have been living in their present home for five years or more, with only about 15 percent having moved from other areas during the previous five years. However, few studies have considered this as a driver of fire risk. In bushfire areas, people who own their home make more preparations for bushfire events than people who live in a rented house. Bushnell and Cottrell (2007) also noted that people who had lived in the area full-time and for a long time tended to prepare themselves better for future bushfires.

Additionally, many studies have demonstrated that household composition has a significant influence on the probability of residential fires. For instance, Goodsman et al. (1987) found that large households with several adults and children potentially have a higher likelihood of a fire occurring than do the small family households. Similarly, Corcoran et al. (2011a) showed that household structure is a significant factor in the occurrence of fire incidents. Residential fires caused by children occur most often during weekdays when children may be at home alone because their parents are working (Asgary et al., 2010). Duncanson et al. (2002) studied a cross-section of residential fire incidents and households in New Zealand and found that house crowdedness has a positive correlation with an increase in the level of fire risk. Similarly, Corcoran et al. (2007) and Chhetri et al. (2010) indicated that household structure and family structure tended to determine fire in buildings. Residential fires occur more frequently in areas with a lower proportion of both childless families and car ownership.

According to the relationships between socio-spatial characteristics as a barrier to a propagation of information and as influencing factors on fire risk, the interest of this study is to bridge the relationship to understand fire risk behaviour from a different angle. Major studies have focused on the ecological or environmental factors relating to residential fire risk. This study, however, argues that the propagation of information may be able to explain the observed differential fire risk that exists across urban areas. Fire risk is related not only to ecological or environmental factors but also to the way that risk is perceived socially within a community. Table 2-1 summarises several factors influencing the propagation of information within a neighbourhood.

Table 2-1: Situated context on residential fire risk

Variable	Studies	Main findings	Relation to spatial interaction	Fire risk level	Reference
Residential mix	Kennedy (1978)	- People living in houses of two or more storeys are less likely to interact with others rather than people living in separate houses	Multiple family dwellings ↑, spatial interaction ↓	- Size of families (↑), residential fire risk (↑) - Single-parent households, residential fire risk (↑) - Crowded house (↑), residential fire risk (↑)	Goodsman et al. (1987) AFAC (2009) Corcoran et al. (2007) Chhetri et al. (2010) Corcoran et al. (2011a)
	Helleringer and Kohler (2005)	- Residents living in apartments tend to find it difficult to communicate or interact with others	Living in single-storey house ↑, spatial interaction ↑ Living in an apartment ↑, spatial interaction ↓		
Language	Meischke et al. (2010)	- People with limited English proficiency have difficulty communicating	Limited English proficiency ↑, spatial interaction ↓	Multicultural (↑), residential fire risk (↑)	AFAC (2009) Chhetri et al. (2010) Corcoran et al. (2011a) Corcoran et al. (2013)
Homeownership	DiPasquale and Glaeser (1999)	- Homeowners have more spatial interaction with the neighbourhood than tenants	Homeownership ↑, spatial interaction ↑	Renters (↑), residential fire risk (↑)	Corcoran et al. (2007) Corcoran et al. (2011a)
	Brisson and Usher (2007)	- Homeowners have strong informal communication and interaction with neighbours	Homeownership ↑, spatial interaction ↑		
Residential Density	Kasarda and Janowitz (1974)	- People living in areas with lower population density and smaller community size tend to have closer interactions or relationships with others in the community	Density↓, spatial interaction ↑	Dwellings density (↑), residential fire risk (↑)	Leth et al. (1998) Wong and Lau (2007a) Yazhou et al. (2010) Sufianto and Green (2012) Jones et al. (2013) Ceyhan et al. (2013)
Residential mobility	Pearson et al. (2012)	- People living at the usual same address for an extended period have a larger network and closer interactions within their neighbourhood	Residential period ↑, spatial interaction ↑	-	-

Variable	Studies	Main findings	Relation to spatial interaction	Fire risk level	Reference
	Kasarda and Janowitz (1974)	- Length of residence has positive effects on socio-spatial interaction	Residential period ↑, spatial interaction ↑		
Socio-economic status	Dervin and Greenberg (1972)	- Residents with low-incomes have more frequent interactions with neighbours	income↓, spatial interaction ↑	- Socio-economic status (↑), residential fire risk (↓) - Income (↑), residential fire risk (↑) - Education (↓), residential fire risk (↑)	Duncanson et al. (2002) AFAC (2009) Corcoran et al. (2007) Asgary et al. (2010), Corcoran et al. (2011a) Corcoran et al. (2011b)
	Kasarda and Janowitz (1974)	- Higher status individuals tend to have smaller networks and less interaction within their communities	Socioeconomic status ↑, spatial interaction ↓	- Disadvantage (↑), residential fire risk (↑) - Advantage (↑), residential fire risk (↓)	Chhetri et al. (2010) Wuschke et al. (2013)
	Chatman and Pendleton (1995)	- Poorer people make better use of interpersonal communication	Socioeconomic status ↓, spatial interaction ↑		
	Fischer (1982)	- The more educated people have a larger network	Education↑, spatial interaction ↑		
	Dekker and Bolt (2005)	- The unemployed are likely to have close relationships because they have more frequent social interactions within their neighbourhood - Lower-income groups tend to have more networks and communication within the community	Employment status ↓, spatial interaction ↑ Income↓, spatial interaction ↑		

2.4. CONCEPTUAL FRAMEWORK OF FIRE RISK

Overall, understanding residential fire risk is a complex task as it requires an assessment of risk at multiple levels ranging from the individual to a neighbourhood or community. There are several substantial gaps in the understanding of fire risk that require more sophisticated analysis, which comprises not only of who is at risk of fire but also how the fire risk is constructed in time and space. Two further research questions remain: How does the experience of a fire incident impact on future perception of fire risk? How do neighbourhood characteristics in a situated context contribute to enhancing a propagation of fire risk information within the community? To address these questions, this study argues that fire risk is not only affected by an individual's perception and experiences but is also shaped by the local learning process at a community level. The perception of fire risk is therefore grounded in space relation, time specificity and the situated context.

Figure 2-4 illustrates the proposed conceptual framework of fire risk in the space context, time-specific context, and situated context of social-spatial barriers to the propagation of information. Risk information is transmitted over space through the process of information diffusion. Individuals exchange experience or information about fire and fire risk within their neighbourhood. The information then spreads from one group to other groups; from a local to a global level. The successful diffusion of information, based on local learning, shapes the perception of fire risk.

The transmission of risk information occurs over time. A past fire experience or information about fire risk is processed cognitively. It will be stored in either short or long-term memory depending on a range of internal and external factors such as negative impact, trusted sources, and others. It is also dependent on the ability of an individual to remember and recall fire incidents. Thus, the retention of information shapes the way that an individual perceives risk information. If individuals decide to accept the information, they often respond by changing their risk perception and behaviour, such as being more aware of risk and taking further actions to reduce similar risk in the future.

However, in regard to the shaping of risk perception through information processing, the diffusion and retention of information faces obstacles related to the spatial-social characteristics of the neighbourhood. Socioeconomic status, home ownership and long-term duration of residency facilitate spatial interactions among residents, whilst other factors prevent information sharing and an increase in risk awareness. Finally, risk perception determines the likelihood of a future fire occurrence. The successful processing of information about fire risk over time and space decreases the probability of a future fire occurrence within the neighbourhood. Individuals are more aware of and prepared for similar incidents by learning from the message conveyed about a past fire incident or learning from their own experience.

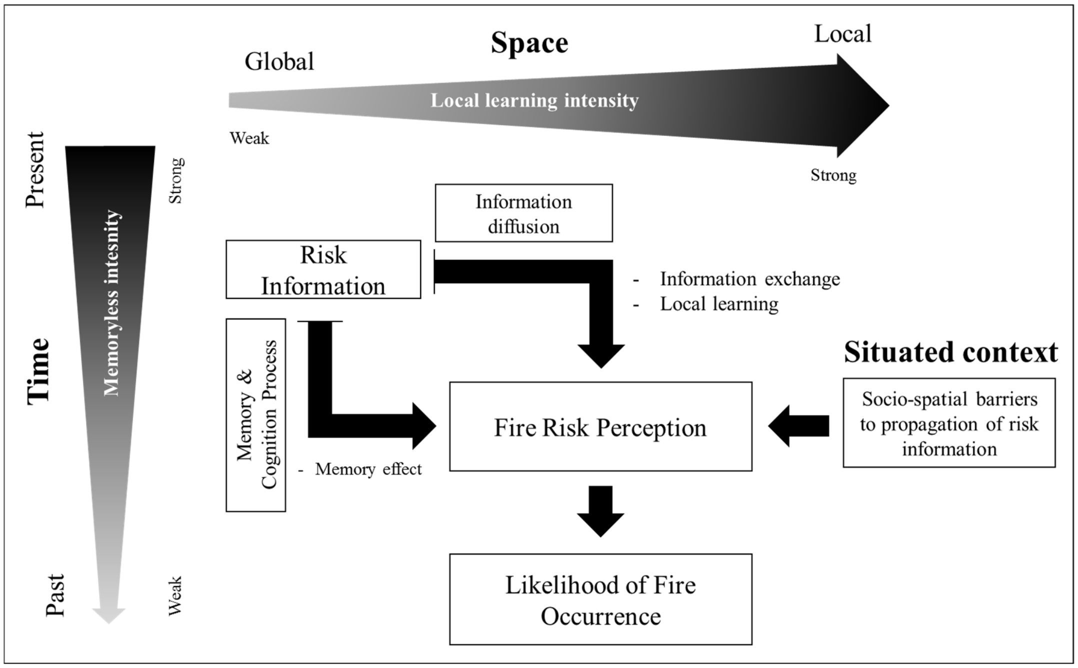


Figure 2-4: Proposed conceptual framework of fire risk

2.5. SUMMARY

Space and time are the two keys, yet inadequately understood, dimensions of fire risk. Most of the previous studies have modelled and mapped spatiotemporal fire patterns or their association with individual or neighbourhood characteristics. However, how fire events and their patterns occur over time and space, and the way they influence fire risk, are largely unknown. For example, how do past fire events within the local area influence the subsequent occurrence of fire incidents? People can recall things, episodes or events that occur in recent time and in their neighbourhood. However, this ability to remember and recall information starts to fade with time. Time is the primary driver of information retention and recall. Memory is heavily dependent on the frame of time. People are more likely to know and retain information about a fire incident when it occurs in their neighbourhood or when they are directly or indirectly affected. Space and time are therefore fundamental in shaping the perception and awareness of fire risk. Adherence to space and time, in turn, might lead to better prevention and preparedness to help mitigate fire risk.

The variability in fire risk is not only space-driven and time-dependent but is also context-specific. The situated context that differentiates neighbourhoods influences the perception of fire risk. This context provides the arena for spatial interaction that shapes the levels of communication and exchange of information. Some factors such as socioeconomic status, long-term duration of residency, and home ownership facilitate spatial interactions among residents while other factors inhibit information sharing and risk awareness. Effective risk communication requires a more targeted strategy to reach out to communities living with a greater risk of fire. This study, therefore, provides a new perspective on modelling fire risk by considering space-dependency, time-specificity and the situated context within which a fire occurs.

The next chapter discusses the modelling technique applied in order to understand the residential fire risk.

CHAPTER 3
APPROACHES AND METHODS OF FIRE RISK MODELLING

3.1. INTRODUCTION

This chapter discusses the existing approaches and methods of modelling residential fire risk. It provides a brief overview of existing analytical techniques used for mapping and computing residential fire risk. It evaluates the benefits and limitations of each of the approaches and the associated methods. The methodological gap in residential fire risk modelling techniques is also drawn from the literature review with the purpose of developing a Markov chain modelling framework.

This chapter consists of four sections. Section 3.2 discusses the recent research and analytical tools used in previous studies. The advantages and limitations of each method are also drawn in this section. Section 3.3 highlights the gap in fire risk modelling. Section 3.4 summarises and concludes this chapter.

3.2. RECENT FIRE RISK MODELS AND ANALYTICAL TOOLS

Expressing fire risk in a way that can be understood by the public is a challenging process. Generally, residential fire risk is defined as a combination of the probability of fire occurrence and its expected consequences. At the most basic level, fire risk has been quantitatively measured as the count of fire incidents (Corcoran et al., 2011a, Duncanson et al., 2002), fire rates (Chhetri et al., 2010, Corcoran et al., 2013, Špatenková and Virrantaus, 2013), and fire probability (Rohde et al., 2010; Lin 2005). Jennings (2013) and Clark et al. (2015) have reviewed a number of relevant studies and summarised the key differences in various residential fire risk models built to investigate and examine residential fire risk and its associated drivers. Generally, the modelling approaches are categorised into either deterministic or probabilistic. The next section discusses each approach in detail, including its advantages and limitations.

3.2.1. Deterministic approach

The deterministic approach is one where every set of the variable state is uniquely determined by parameters in the process (i.e. model) and by sets of the previous state of these variables (Renard et al., 2013). In a deterministic process, the model will always have the same outcome for a given set of initial conditions. The deterministic approach is often classified as a classical statistical model approach which is the prevailing practice of modelling fire incident by representing it with fixed values. The model might be also represented by the probability distribution function, which assigns probabilities to a value of random variable. For instance, the exponential distribution is the most frequently used in relation to the reliability of incidents model, while normal distribution is applied for modelling the duration and the lifetime of the process.

The deterministic approach may include some of the methods described below.

3.2.1.1. Kernel Density Estimation methods

Kernel density estimation is traditionally used in a general statistical context to obtain estimates of univariate or multivariate probability functions from a set of observed samples. It is a non-parametric method used to estimate the probability density function of a random variable. Kernel density estimation is a data smoothing problem where inferences about the population are made, based on a finite data sample (Gatrell et al., 1996). This method employs the three-dimensional function (i.e. the kernel), which weights events within a certain "*sphere of influence*". The distance between a point of the event and observed samples, thus, play a role in the estimation process. The bandwidth (i.e. a distance between a point and observed samples) is a free parameter, which has a strong influence on the resulting estimates. The key limitation of the kernel density estimation is that it heavily depends on the bandwidth. Choosing the right bandwidth is highly subjective and no procedure has yet being developed and agreed to fit for every situation. Therefore, kernel density estimates are not consistent with the exception where bandwidth is fixed. In fire risk modelling, Corcoran et al. (2007) used Kernel Density Estimation (KDE) to understand spatial and temporal patterns of different types of fire incidents. The study applied the model to fire incident datasets of South Wales, United Kingdom. They modelled a correlation of fire incidents with socio-economic characteristics such as unemployment, non-home ownership, non-car ownership, and household overcrowding according to Townsend's index of deprivation.

In case of this research, the kernel density estimation is not considered as a technique to estimate the probability of fire occurrence due to this technique only applies for data smoothing problem where inferences about the fire incidents across areas are made based on a finite data sample. Therefore, it is not fitted with the objective of this research as mention in Chapter 1.

3.2.1.2. Regression techniques

The regression analysis is a statistical process for estimating the relationships among variables. Here the focus is on understanding the relationship between a dependent variable and one or more independent variables. Practically, the regression model relies on determining the dependent variable (often noted as Y) by producing the unbiased minimum sum of error square in Y in regard to the independent variable (X). For unbiased observations, the prediction should be equal to the expected value of the dependent variable for a particular set of data.

To understand the behaviour of residential fire risk pattern and its relationship with geographical characteristics, Corcoran et al. (2007), in their study on South Wales in the United Kingdom, applied regression analysis to examine the association between geographical fire patterns and socio-economic characteristics such as car ownership, education, ethnicity, household structure, family structure, age, and owner-occupied housing. Similarly, Chhetri et al. (2010) applied the regression model to investigate the association between residential fire incidents and socio-economic characteristics in South East Queensland in Australia using five variables as predictors; these were unemployment, indigenous population, separated living families, single parents, and families with children under fifteen. The model was also used to investigate the impact of socio-economic clustering consisting of culturally diversified and economically disadvantaged suburbs, traditional family living in traditional suburbs, and high-density inner suburbs with a social housing component. The limitation of those existing study is the selection of dependent variable. Those studies employ fire density or fire rate as dependent variable. However, the selection of those measures as dependent is not fitted with the definition of fire risk used in this study as mention in Section 2.2.1. Fire risk is defined as the probability of fire occurrence so that it considers fire as a random phenomenon. Therefore, it requires a modification in selecting the dependent variables to have a better analysis on residential fire risk.

The regression model is based on a set of assumptions: normality, homogeneity and independence of residuals. Violation of these assumptions leads to inefficient and biased estimators, thus resulting in inaccurate estimation of the model parameters by the regression model (Montgomery et al., 2012). It is important to note that the coefficient estimates in the regression model are assumed to be universal. Because of the spatial stationary assumption, the regression model derives the parameter for a global condition across space over which measurements are taken. In fact, the global parameters might not represent an actual situation because of non-stationary spatial data in such relationship across space. Also, the global model (i.e. regression model) often does not account for local variation over space. Figure 3-1 shows an example of how global model estimates parameters for a global condition of model house price. Nevertheless, there are two clusters: location 1 with a low population density and location 2 with high population density. Consequently, each cluster has different models based on its local variation (i.e. population density). Therefore, it is appropriate to perform local analysis so that it can capture local processes rather than using a global analysis which assumes spatial stationarity.

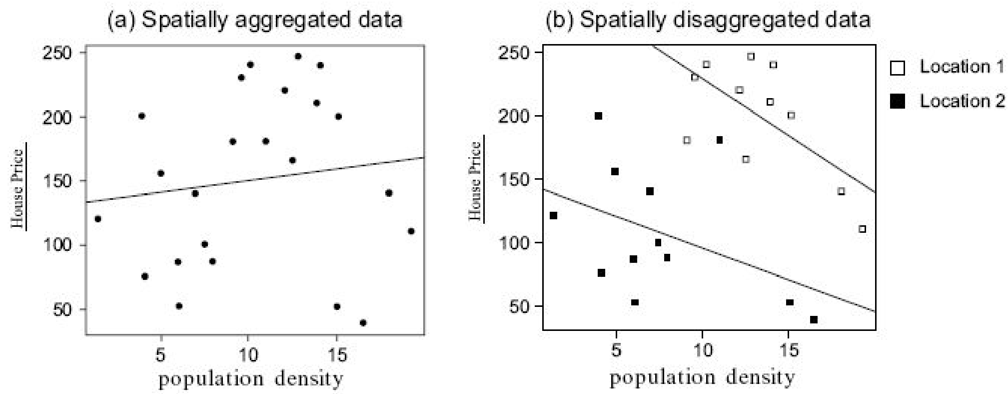


Figure 3-1: Illustration of global regression model and local model

The Geographically Weighted Regression (GWR) is an extended version of the traditional regression model as it takes spatial heterogeneity into account by incorporating the spatial location of data. Wheeler and Tiefelsdorf (2005) pointed out the development of GWR originated from the traditional regression model and smoothing techniques. It was a further improvement of those models with its continuous development of statistical measures such as maximum likelihood estimation of the kernel bandwidths, spatial autocorrelation among the residuals, generalized linear model specification and test statistics for spatial non-stationary and heterogeneity of the local model parameters.

In a recent study, in extending the spatial analysis of fire risk, Špatenková and Virrantaus (2013) have applied Geographical Weighted Regression (GWR) to examine how residential fires are influenced by variables such as building type, year of construction, population density, household type, education, unemployment, and income level. The GWR was used to capture a deeper understanding of local dependence and spatial autocorrelation in the distribution of fire occurrence. Figure 3-2 illustrates the magnitude of parameter values of population density of the model on dwelling fires. A positive value indicates that high population density has a strong influence on increased residential fire risk at a certain area, whilst negative values indicate that high density of population significantly reduces fire occurrence. The direction of the strong effect is moving from the north east region to the southern region.

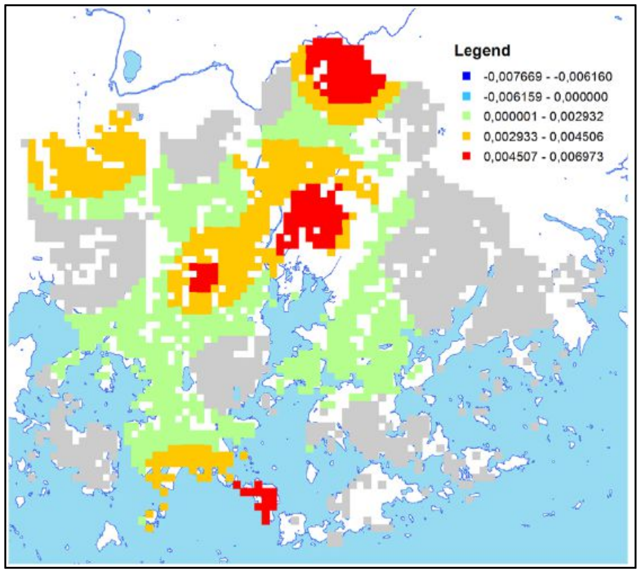


Figure 3-2: Parameter value of population density for GWR model on residential fire (Špatenková and Virrantaus, 2013, p.59)

3.2.1.3. Geo-demographic methods

Geo-demographic analysis is the method used to analyse people based on the statistical classification of a certain area. The method aims to capture the necessary socio-economic dimensions of neighbourhoods. The classification is generated primarily from census data, surveys, or other sources. Nevertheless, the theoretical perspective about the importance of classification as an indicator of the association between spatial characteristics (i.e. neighbourhood characteristics) and, for instance, fire incidence has remained a relatively ignored areas of research. Most previous studies used traditional segmentation approaches to identify a trend in fire incidence within a population which might have similar attributes such as gender, age, socioeconomic status, and others. Geo-demographic classification has extended the traditional approaches by including information on behaviours, habits, and other factors so that it potentially offers a robust understanding of subgroups within the population.

Geo-demographic classification focuses on the distinctiveness of areas and offers new insight into social processes using a range of demographic attributes. The attributes, thus, are used to classify small geographic areas by predominant locality and their residents' characteristics. The main advantages of the geo-demographic classification method are that it can be used to not only explain a particular outcome but also to explore and describe the details of the outcome.

The geo-demographic classification method is increasingly being employed by a number of fire agencies to assist with operational and strategic planning, especially in the UK. Corcoran et al. (2013) have applied the geo-demographic method to investigate the potential association between fire incidents and socio-economic patterns. The database of fire incidents in the UK demonstrated a clear trend whereby the most deprived areas or groups had the highest rates of fire incidents (see Figure 3-3). A complex pattern of fire incidents is captured in relation to certain factors such as social cohesion and social capital.

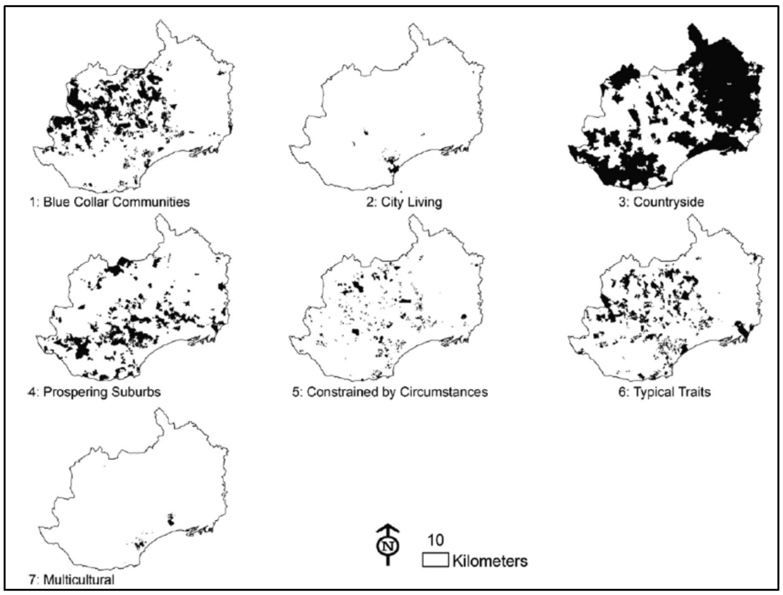


Figure 3-3: The distribution of supergroup classification for South Wales using geo-demographic analysis (Corcoran et al., 2013, p. 42)

Due to it can only be used to investigate the spatial pattern of fire risk, the method is not fitted with the objective of this study which is aimed to estimate the probability of fire occurrence and to investigate the fire risk pattern both in time and space. On the other hand, this technique also has a limitation in explaining the outcome of the result which is based on spatial characteristic. The method ignores time dependence on fire risk which can be viewed through the history of fire incidents over space.

3.2.2. Probabilistic approach

A probabilistic approach, generally, is a probability-based model, which traditionally is used to describe phenomena that evolve over time and space. In the probability approach, there is some indeterminacy in that if the initial condition (or starting point) is known, there are several ways or directions in which the process may evolve. Therefore, randomness is a factor and the variable states are not described by unique values. This is often known as a forecasting approach used to assist with decision making to avoid negative consequences such as loss (Marhavilas and Koulouriotis, 2012).

Some of the methods used in a probabilistic approach are explained below.

3.2.2.1. Bayesian network

The Bayesian network is also commonly used in fire modelling. It is a probabilistic graphical model based on Bayesian inference. The principle of this method is to establish a probabilistic relational network to quantify the intricate cause-effect relationship among various factors. The event tree model is the technique most commonly used in the Bayesian network. The event tree model uses a decision tree and logically develops the possible outcome of an initiating event. The event tree model is a graphical representation of the logic model that identifies the possible outcomes based on the initiating event. The initiating event, itself, is referred to as the starting point. It is known as an event tree model because the graphical representation of sequential events grows like a tree as the number of events increases. The tree consists of an initiating point, probable subsequent events, and the final outcome. Each event in the probable sequence is independent of the others. The final results depend on the initiating event and the sequence following the starting point. The occurrence probability, therefore, is calculated by multiplying the probabilities of all subsequent events along a specific path. This model is a very effective means of describing the order of events with respect to time (see Figure 3-4).

In fire risk modelling, Dickson et al. (2006), Rohde et al. (2010), Cheng and Hadjisophocleous (2009), Hanea and Ale (2009), and Matellini et al. (2013), employed a Bayesian network to examine the probability of fire. Those studies apply the technique for understanding fire in buildings which the event path (i.e. from starting point to the outcome) can be defined clearly. Nevertheless, this technique is not suited for residential fire risk modelling at large scale due to it is difficult to define the event path of fire sequence. The occurrence of fire incident at large space has large number of the possibility path and direction over space.

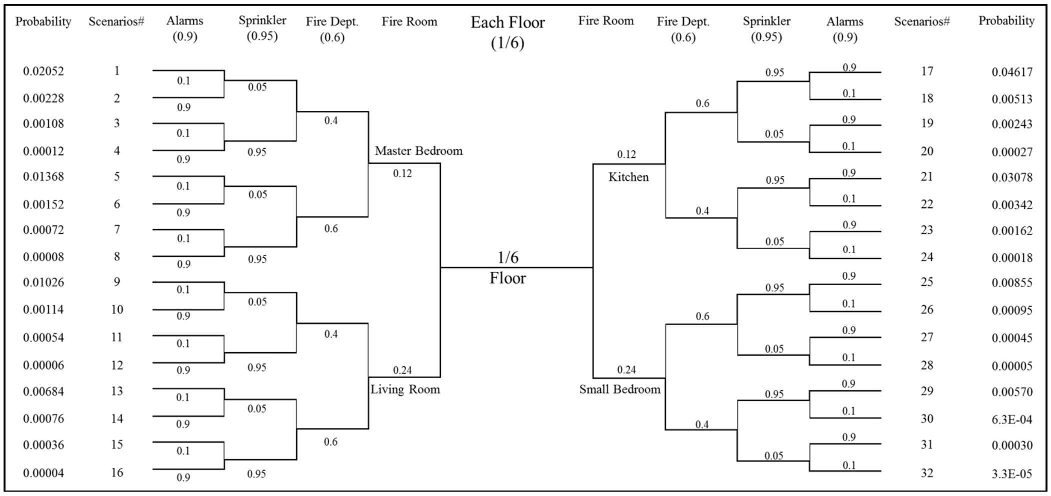


Figure 3-4: An example of event tree model to analyses fire risk in the building (Li et al., 2013, p. 613)

3.2.2.2. Point pattern analysis

In some applications, the observations are recorded by means of a counting process, such as fire occurrences in an urban area, criminal events in certain areas, or road accidents. The probability function approach is appropriate for solving the problem. As discussed in the earlier section, not all observations can be assumed to have a normal distribution. Some might have other distributions because of the skewness of observations. The Poisson model is typically used for a process which has right-skewed distribution and rare events and is applied to a series of random events occurring over time.

Very few studies have used point pattern analysis to examine the spatial distribution of fire incidents. Špatenková and Virrantaus (2013) formulated a fire risk model by considering fire incidents as a spatial point process. A non-stationary Strauss process, which allows flexibility in modelling of spatial dependence, was applied to calculate the density of fire incidents. Applying a non-Strauss process to the data, the study modelled the dependence of fires on selected explanatory variables such as income, population density, and building type. Figure 3-5 shows the fire density hot spots estimated by using interaction parameters of the model. The high value of the interaction parameters indicates the strength of interaction between fire incidents and spatial covariates such as population, income and building type.

Although, this technique has advantages in understanding fire risk behaviour as it assumes fire incidents as a counting process, the technique is appropriate for spatial process (Špatenková and Virrantaus, 2013). Therefore, it is not fitted with the objective of this study which needs temporal and spatial analysis of residential fire risk.

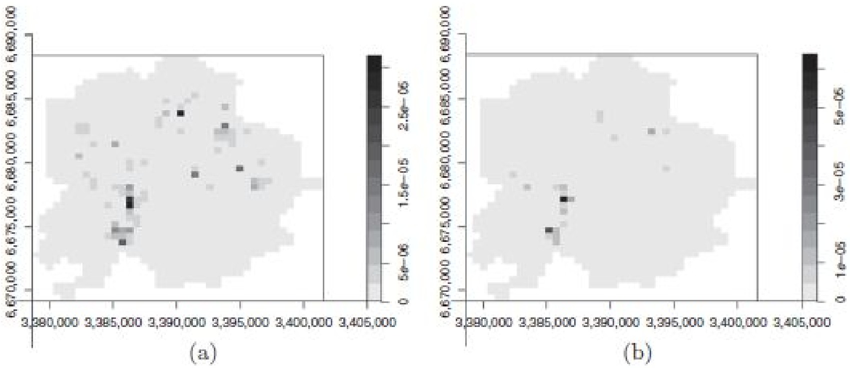


Figure 3-5: Fitted density function of residential fire and selected covariates: (a) population income and (b) building type, using a Strauss process (Špatenková and Virrantaus, 2013, p.57)

3.2.2.3. The Diggle function and Ripley function

The kernel density estimation has the limitation that its estimates are not consistent except for fixed bandwidths. To solve the inconsistency of kernel density estimates, Diggle's D-function and Ripley's K function are modifications of the kernel function. The idea of this method is to apply the behaviour of the general spatial-temporal process including the first-order moment and the second-order moment. The first-order moment describes the way in which the expected value such as mean or average of the process varies across space within a time interval. The second-order moment describes the covariance (or correlation) between two values of the process at different points in space and at different time intervals. The second-order properties measure the types and strength of the interaction between events in the point process. Therefore, the second-order properties are particularly interesting if one wants to study the clustering of or interaction between events. Here, a spatial-temporal pattern may arise from each moment (e.g. the trend arises from the first-order moment and the correlation structure arises from second-order moment) or from a combination of those moments. Furthermore, by considering the first-order moment of a point process, Gatrell et al. (1996) showed that there is a mathematical relationship between the second-order moment and kernel function, termed the K-function (i.e. Ripley's K-function).

In residential fire risk modelling, Ceyhan et al. (2013) applied Diggle's D-function and Ripley's K function to analyse the spatiotemporal patterns of residential fires in the Çankaya Municipality of Ankara, Turkey. Diggle's D-function was used to detect fire patterns over time and Ripley's K function was applied to examine the trend of fire incidents according to space and time dimensions. Figure 3-6 illustrates the K-function for distance and temporal K-function for time differences in years. The values of the estimated K-function tend to increase as time and distance increase. This indicates that the fire locations tend to be clustered in terms of time and space. The colour-coded grid shows the variability of the estimated K-function where the high value of spatio-temporal K-function indicates a large distance between points (i.e. fire incidents) and moderate time difference. Their study demonstrated that there is a significant space-time interaction between residential fires for the time at the month level, meaning that residential fire within a certain distance in different months has a significant influence on others. However, there is no significant interaction between fire incidents for time in term of week or day. Their study can assist fire management to design different strategies for different months of the year and different sections of the study region.

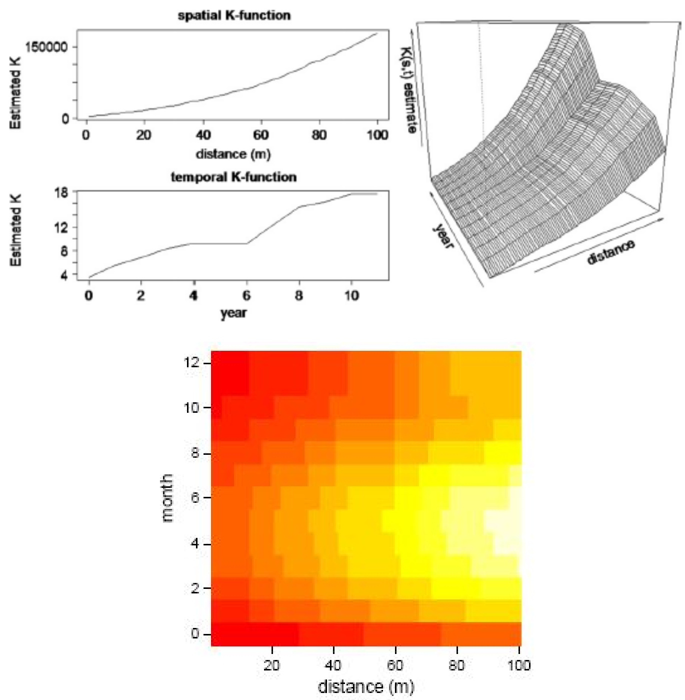


Figure 3-6: Spatial and temporal K-function and the perspective plot of K estimate as a function of year and distance (Ceyhan et al., 2013, p.235-236)

This technique is used only for investigating the temporal and spatial pattern of fire incidents. It cannot be used to calculate fire risk, in this study it refers to the probability of fire occurrence. Therefore, it is not fitted with the objective of this study.

To sum up, Table 3-1 summarises the advantages and limitations of the abovementioned techniques used in residential fire risk modelling.

Table 3-1: Advantages and limitations of some techniques used in residential fire risk modelling

Model	Advantages	Limitations	References	Reason not applying
Kernel Density Estimation	- An effective visualization method to cluster fire incidents to generate the surface of risk levels - employs the three-dimensional function (i.e. the kernel) which weight events within a certain sphere of influence - obtains estimates of univariate or multivariate probability function from a set of observed samples	- Highly dependent on the bandwidth; i.e., choosing the right bandwidth is subjective kernel density estimates are not consistent except for fixed bandwidth	- Corcoran et al. (2007) - Asgary et al. (2010)	used only for investigating the temporal and spatial pattern of fire incidents
Diggle's D function and Ripley's K function	- detects fire patterns over time and Ripley's K function was also applied to examine the trend of fire incidents in space and time dimension - explores fire clustering patterns with more statistical significance for formulating any decision rather than kernel density estimation -	- may require user-defined parameters to further test various hypotheses - has the shortcoming of indicating fire clusters without sufficient consideration of background population	- Ceyhan et al. (2013)	used only for investigating the temporal and spatial pattern of fire incidents. It cannot be used to calculate fire risk as it is the objective of this study
Point pattern and Poisson process	- allow flexibility in modelling of pairwise interactions - used for a process which has right-skewed distribution and rare events - applied to a series of random events occurring in time	- assumes constant interaction within a fixed interaction radius	- Foody (2003) - Hanham and Spiker (2004) - Yu and Wu (2005). - Wang et al. (2005) - Wheeler and tiefelsdorf (2005) - Hang and Shi (2014)	Appropriate only for spatial process while the objective of this study needs temporal and spatial analysis of residential fire risk
Geo-demographic classification	- allows information on behaviours, beliefs, habits, and preferences to be incorporated potentially offer a	- needs robust validity in particular prior to being used in public sector	- Corcoran et al. (2013)	provide result based spatial analysis only and ignores time dependence on fire risk while this study considers

Model	Advantages	Limitations	References	Reason not applying
	more robust understanding of subgroups within the population - capacity to offer new insights into social processes using a range of demographics and contextual variable to classify small geographic areas by the predominant characteristics of the locality and its residents	- has limitation in explaining the outcome of the result		temporal and spatial dependence of fire risk
Regression	- simply and widely applicable model for spatial data analysis - the dependent variable is modelled as a function of the independent variables, corresponding parameters and an error term	- a presumption about the function form of regression equation must be made at the outset - based on a set of assumptions: normality, homogeneity and independence of residuals - the assumption of no error in measurements of fire risk by OLS model is almost impossible to achieve in reality	- Goodsman, Mason and Blythe (1987); - Fernandes and Leblanc (2005); Chhetri et al. (2010); Corcoran, Higgs and Higginson (2011)	requires a modification in selecting the dependent variables to consider fire risk as a random variable
Geographically Weighted Regression	- allows unveiling and modelling spatial variations existing in variations existing in a relationship over space - captures local spatial variation across space - allows in-depth investigation local variation in the relationships across space - capable of identifying non-stationary spatial data in the	- some observed points over space have low influence in deriving the parameters and the outliers have a great impact on estimating localized model parameters - the interpretation requires more contextual information and underlying information	- Foody (2003) - Hanham and Spiker (2004) - Yu and Wu (2005). - Wang et al. (2005) - Wheeler and Tiefelsdorf (2005) - Hang and Shi (2014)	requires a modification in selecting the dependent variables to consider fire risk as a random variable

Model	Advantages	Limitations	References	Reason not applying
	association among explanatory variables	- highly relies on the weighted kernel function such that the bandwidth should be properly considered to get desired local variation - not suitable for extrapolating a relationship beyond the region for which model has been developed		
Bayesian Network	- very effective for describing the order of events with respect to time - a graphical representation of the logic model	- final results depend on the initiating event and the sequence following the starting point	- Dickson et al. (2006) - Cheng and Hadjisophocleous (2009) - Hanea and Ale (2009) - Rohde et al. (2010) - Matellini et al. (2013)	difficult to define the event path of fire sequence at large space which has large number of the possibility path and direction over space

3.3. RESEARCH GAPS: FIRE RISK MODELLING

The review of the existing studies and the methods applied to model fire risk patterns shows several substantive gaps that require the development of more sophisticated analysis to incorporate spatial and temporal dependence. This will enable us to understand how fire risk is constructed in time and space. The critical points of existing seminal work on residential fire risk modelling are discussed below.

The first research gap identified in the extant of literature on fire risk modelling relates to the limited ability to quantifying residential fire risk as a probability. Although fire risk has been modelled rigorously, the notion of fire probability represented in the existing fire risk models showing the randomness of the fire occurrence and its drivers remains underexplored. The use of the traditional means of estimating fire risk such as the count of fires, however, is potentially misleading because areas differ from one another in terms of population or dwelling density. The fire count, therefore, cannot identify the variations in relation to the size of the population. Evidently, more populated areas are likely to have more residential fires than less populated areas. To solve this problem, a few studies such as Chhetri et al. (2010), Špatenková and Virrantaus (2013), and Corcoran et al. (2013) used other measures to determine the levels of fire risk. They computed a ratio of residential fires to the population size in a particular area. This ratio shows the proportion of fire in terms of the total number of residential fires per 1,000 people, for instance. However, this measure does not consider fire occurrence as a random phenomenon which is affected by several uncertain factors. Hence, the probability of fire occurrence should be calculated to account for the randomness of the phenomenon. Considering fire risk as probabilistic phenomenon might also potentially improve the accuracy and reliability of fire risk modelling (Corcoran and Higgs 2013; Jennings 2013).

The second research gap concerns with a relative paucity of studies that simultaneously integrate space and time dimensions in fire risk modelling. Fire risk has not been investigated as a Markov chain process to model the probability of residential fire occurrence. The application of the Markov chain model could enable capturing the spatial and temporal aspects of fire risk. Often, residential fire risk is modelled by considering only spatial dependence such as the variability in neighbourhood characteristics or environmental conditions (i.e. temperature). The effect of past events on the likelihood of subsequent fire incidents within a local area has been largely overlooked in previous studies. The Markov chain can be used within a frame of space and time to model sequential dependencies that influence the spatial dynamic of a fire risk as a geographic phenomenon.

Followed this argument, the third research gap is associated with the lack of knowledge about the spatial-temporal dependence (when and where), which in turn affect as the nature and characteristics of neighbourhood effects and memory-less effect (the effect of past events within the local area). When a fire occurs in a neighbourhood, the likelihood of a fire occurrence within a certain distance and time is affected. This makes the phenomenon of fire space- and time-dependent. Building on this stochastic approach with the spill-over effect over time and across space, this study develops a fire risk modelling framework based on the Markov process to estimate the levels of residential fire risk.

The fourth research gap is related to the recency of literature on time and memory effect related to fire risk. Recent study on the relationship between fire risk and memory effect is done by Clode (2010), but her study focuses on how bush fire has psychology impact to individuals. She argues that individuals tend to memory their bush fire experience in a certain period. In case of residential fire risk, the relationship between fire risk and memory effect has been overlooked. Research focusing residential fire tends to call for more spatial analysis of fire behaviour. The recent study done by Clark et.al (2015) mentions that risk is temporal and follow the way in which individuals retain the information about fire experience. Therefore, there is a little reference on time and memory effect linking to residential fire risk.

The fifth research gap, regardless of how the techniques are applied, another critical point is that very limited attention to date has been paid to residential fire risk's theoretical underpinning. There is a lack of well-defined theory that has capacity to understand and explain the behaviour of residential fire risk pattern over urban space. Much of the existing published research has made only use of a range of socio-economic variables to explore their relationships with residential fire risk. Based on such studies, it is suggested that fire risk can be seen as an outcome of social and economic problems. Low socioeconomic status, poor housing quality and unstable family circumstances may provide a sound basis for explaining the areal differentiation in fires in urban areas. Hence, fire risk is possibly socially constructed and has a meaning embedded in the way society is socially and economically stratified and spatially fragmented. However, high socio-economic status is not always related to low fire risk; nor can it be said that every disadvantaged area is more prone to fire.

There is another perspective that can be used to understand behaviour associated with fire incidents. In the literature on residential fire risk and its associated dominant factors, Clark et al. (2015) suggested that it is not only the physical and social environments that influence fire risk; it is also affected by wider influences such as membership of particular social groups. Some factors such as socioeconomic status, long-term duration of residency, and home ownership facilitate spatial interactions among residents whilst others inhibit information sharing and risk awareness. Effective risk communication requires a more targeted strategy in order to reach out to communities at a greater risk of fire (Rhodes and Reinholtd, 1998). Therefore, in order to acquire a better understanding of residential fire risk patterns across urban space, theoretical work should be commenced by drawing upon and translating perspectives existing elsewhere in the social studies such as diffusion of information.

The sixth research gap relates to the lack of spatial statistics to capture the local spatial variability of fire risk and its associated drivers. Most of the previous fire risk studies used a global model (i.e. Ordinary Least Squares) to examine the relationship between fire risk and its associated drivers and successfully identified dominants factors which increase or lessen fire risk levels. However, the models assumed that a global condition existed across the study area. They overlooked the local variation over space as well as the fact that different locations have different characteristics. These studies did not consider that local variations play a vital role in shaping the fire risk. Therefore, Geographically Weighted Regression is needed to capture the local variability which might influence the fire risk level.

To sum up, Table 3-2 summarises the existing studies on residential fire risk modelling. In the 'Objective' column, it can be seen that the main purpose of previous studies was to investigate the relationship between fire risk and its associated factors. Some of them attempted to find ways to estimate the probability of fire occurrence. This is particularly the case for studies on residential fire risk in the building model which is concerned with fire safety scenarios. Few studies attempted to determine residential fire probability on a large scale such as the city level. Under the 'Risk Measurer' heading, the fire count and rate of fire were mainly used to quantify residential fire risk when dealing with large-scale areas of interest. The probability of fire occurrence was applied only in the modelling of fire risk in buildings.

In the context of space and time dependence, reveals that those two dimensions have been overlooked. The developed models did not consider fire risk as a function of space and time. Instead, most models relied on the situated context related to fire risk. The previous studies considered the situated context as a main variable in the fire risk function in order to determine the pattern of residential fire risk. Interestingly, socio-spatial characteristics such as socioeconomic status, household structure, dwelling characteristics (i.e. type of dwelling), dwelling density, and ethnicity were a focus of spatial analysis in an attempt to understand the behaviour of residential fire risk in the situated context. Some studies such as Wuschke et al. (2013) extended their analysis by having insight into different angle such as from criminology perspective to understand the behaviour of fire risk.

Overall, Table 3-2 shows the existing models for residential fire data at global level. They summarise the spatial characteristics over a whole study area with a single-value statistic. Therefore, this study fills the gaps by developing a model which takes into account the space and time dependence and the situated context. The relationship between fire risk and spatial characteristics is understood from the perspective of the theory regarding the diffusion of risk information.

Table 3-2: Key studies on residential fire risk modelling

Modelling approach/method	Studies	Objective	Risk measure	Dependence		Situated context	Spatial characteristics used	Variation level
				Space	Time			
Descriptive statistics	Duncanson, Woodward and Reid (2002)	Fire risk-associated factors	Count of fire	x	x	✓	Socioeconomic status, ethnicity, education, tenure	global
Descriptive statistics	Corcoran et al. (2011)	Fire risk-associated factors	Count of fire	x	x	✓	Socioeconomic status, disadvantaged/advantaged areas, calendar events, weather	global
Hotspot analysis	Wuschke, Clare and Garis (2013)	Fire patterns	Count of fire	x	x	✓	Crime occurrence	global
Regression	Goodsman, Mason and Blythe (1987)	Fire risk-associated factors	Probability of fire	x	x	✓	Family structure, building type	global
Regression	Corcoran et al. (2007b)	Fire risk-associated factors	Count of fire	x	x	✓	Socioeconomic status, disadvantaged/advantaged areas	global
Regression	Chhetri et al. (2010)	Fire risk-associated factors	Rate of fire	x	x	✓	Disadvantaged/advantaged areas, ethnicity, family structure	global
Regression	Corcoran, Higgs and Higginson (2011)	Fire risk-associated factors	Count of fire	x	x	✓	Disadvantaged/advantaged areas, family structure, car ownership, education, tenure, building status, ethnicity	global

Modelling approach/method	Studies	Objective	Risk measure	Dependence		Situated context	Spatial characteristics used	Variation level
				Space	Time			
Point process and geographically weighted regression	Špatenková and Virrantaus (2013)	Fire risk-associated factors	Rate of fire	x	x	✓	Population density, building type, socioeconomic status, education, Family structure	local
Poisson process	Lin (2005)	Fire probability in building	Probability of fire	x	x	✓	Building type	global
Beta distribution	Rohde, Corcoran and Chhetri (2010)	Fire probability	Probability of fire	x	x	✓	Number of buildings, number of inhabitants	global
Monte Carlo	Au et al. (2007)	Fire risk in building	Probability of fire	x	x	✓	Temperature	global
Markov chain	Guanquan and Jinhua (2008)	Fire probability and scenario	Probability of fire	x	x	✓	Fire system	global
Bayesian Network	Cheng and Hadjisophocleous (2009)	Fire probability in building	Probability of fire	x	x	✓	Building structure	global
Bayesian Network	Hanea and Ale (2009)	Fire scenario	Probability of fire	x	x	✓	Location, structure, fire system	global
Bayesian Network	Cheng and Hadjisophocleous (2011)	Fire probability in building	Probability of fire	x	x	✓	Building structure, heat, fuel	global
Bayesian Network	Matellini et al. (2013)	Fire probability in building	Probability of fire	x	x	✓	Fire-type, fire system	global
Bayesian Network	Rohde et al. (2010)	Fire probability	Probability of fire	x	x	✓	No. Building, no. Inhabitants	global

Modelling approach/method	Studies	Objective	Risk measure	Dependence		Situated context	Spatial characteristics used	Variation level
				Space	Time			
Comaps	Corcoran et al. (2007a)	Fire patterns	Count of fire	x	x	x	-	global
Comaps	Asgary, Ghaffari and Levy (2010)	Fire patterns	Count of fire	x	x	x	-	global
Kernel Density Estimation	Corcoran et al. (2007b)	Fire patterns	Count of fire	x	x	✓	Socioeconomic status	global
Ripley's K function	Ceyhan, Ertuğay and Düzgün (2013)	Fire patterns	Count of fire	x	x	✓	Residential property	global
Geo-demographic analysis	Corcoran, Higgs and Anderson (2013)	Fire patterns	Rate of fire	x	x	✓	Population density	global
Proposed								
Markov chain		Fire risk (probability) estimation	Probability of fire	✓	✓			
Geographically Weighted Regression		Fire risk-associated factors modelling	Probability of fire			✓	Social-spatial barriers to a propagation of information	local

3.4. SUMMARY

This chapter provided an overview of the existing approaches and techniques used to model and understand residential fire risk. There are two major approaches: deterministic and probabilistic. The deterministic approach views problems as a single output for a given set of conditions. Kernel Density Estimation, regression techniques, and geo-demographic method are some examples of the approach. On the other hand, the probabilistic approach considers randomness as a main factor in analysing and understanding phenomenon. The solution does not depend only on initial conditions. Rather, there is indeterminacy in that there are several possibilities determining the outcome. Point pattern analysis, the Diggle function and Ripley function, and Bayesian Network are some examples of the approach.

This chapter also provided an overview of the gaps in residential fire risk modelling: (i) the limited ability to quantify residential fire risk as a probability; (ii) poor integration of space and time dimensions in fire risk modelling; (iii) the lack of knowledge about spatial-temporal dependence which relates to the effect of past fire events within a local area); (iv) the lack of a well-defined theory that can explain the observed differential fire risk over urban spaces; and (v) the lack of spatial statistics to capture the local spatial variability of fire risk. In order to address the gaps, this study employed the combination of Markov chain and the Geographically Weighted Regression to model and understand the behaviour of residential fire risk in space context, time-specific, and the situational. The diffusion of information theory was used to improve the theorisation of residential risk and to explain its patterns.

The next chapter describes the methodology of the study including research design, data collection, and modelling technique.

CHAPTER 4
RESEARCH METHODOLOGY

4.1. INTRODUCTION

This chapter presents a systematic, theoretical analysis of the methods applied to fire incident data. It comprises an analysis of the methods and principles associated with a particular branch of knowledge. It presents an overview of quantitative research, dataset, and introduces the underlying concepts behind the two techniques applied to analyse fire incident data -Markov chain and Geographically Weighted Regression- to estimate and model residential fire risk.

The chapter consists of six sections. Section 4.2 discusses the advantages and limitations of qualitative and quantitative approaches in order to determine the most suitable approach to data analysis and modelling for the purposes of this study. Section 4.3 provides a detailed description of the datasets used for this study. Section 4.4 explains the Markov chain; this is followed by an explanation of the Geographically Weighted Regression technique in Section 4.5. Section 4.6 summaries and concludes this chapter.

4.2. QUANTITATIVE RESEARCH

Quantitative research is, generally, defined as a systematic experimental investigation which mainly uses statistical, mathematical or computational techniques to analyse phenomena (Given, 2008). The objective of quantitative research is to develop mathematical models, build theories, and test hypotheses to explain real-world phenomena. In the philosophical framework, quantitative research is characterised primarily by positivist epistemology (Arghode, 2012). Rawnsley (1998, p. 3) defines epistemology as '… the phrase theory of knowledge to encompass philosophical problems concerned with the origin and structure knowledge'. The dominant epistemology in the natural sciences and the social sciences is positivist (Boyd et al., 1991). Positivist researchers conduct experiments to discover empirically a possible causal law in general laws which can be used to test hypotheses, make predictions and explain phenomena. Positivism links the abstract ideas of the relationship to a precise measurement of the social world. Hence, positivist researchers generally establish a clear separation between science and personal experience (Sobh and Perry, 2006). Johnson and Onwuegbuzie (2004) point out that positivism research is objective, and it is reflected in writing styles that are formal and impersonal and generally use technical terminology to explain findings in a theoretically objective way.

The constructivist approach suggests that knowledge can be constructed subjectively based on experience and is principally of a personal nature (Lupovici, 2009, Pegues, 2007). Constructivist researchers generate findings and seek to construct a world based on perception (Pegues, 2007). Cupchik (2001) highlighted the main distinction between positivists and constructivists is that positivists argue that knowledge is constructed by means of applying the scientific method, while constructivist argue that knowledge is constructed by scientists in various domains. Constructivist researchers generally use the qualitative research method (Seale, 1999).

This study has employed a predominantly quantitative research method for three key reasons as follows:

- A fire risk model to examine the relationship between fire risk and its urban drivers can only be developed only through statistical, mathematical and computational techniques;
- Quantitative methods are better suited to improving the understanding of residential fire risk as a function of space and time, and situated context; and
- Quantitative methods provide a comprehensive analysis of a large database of residential fire incidents and provide statistically significant results.

4.3. DATA

Two data sets are used for this research: residential fire dataset and census data.

4.3.1. Residential fire data

This study used fire incidence data provided by the Metropolitan Fire Brigade (MFB) between June 2005 and May 2015. The residential fire data was obtained from all official fire incident reports provided by 47 fire stations. Since 2005, the residential fire database has been well maintained by the fire agency to ensure accuracy and reliability. Fire incident data consist of attributes such as location, time of the incident, the cause of the fire, types of building, alarm level, number of fatalities, and fire origin. Additional attributes are added to this database such as distance to the city centre, distance to the nearest fire station, etc.

The dataset comprises geo-referenced information on 17,484 fires: 10,760 fires occurred in inner suburbs, followed by 2,883 fires in northern suburbs, 2,282 fires in western suburbs and 1,923 in eastern suburbs.

4.3.2. Census data

When building a probability model for a residential fire, it is advisable to recognize possible factors explaining the spatial and temporal patterns of fire risk. As residential fires are often attributed to human factors, human behaviour and socio-economic characteristics such as age, education, and income, should be taken into account. This study considered spatial indicators such as resident mobility, the level of proficiency in English, residential density, type of dwellings, and tenure status, which either impede or facilitate information diffusion within a local area.

The spatial data for geographical characteristics employed in this study were obtained from the online Australian Urban Research Infrastructure Network (AURIN) portal. AURIN is a national collaboration delivering e-research infrastructure to empower better decisions for Australia's urban settlements and their future development. AURIN collaborates with more than 60 institutions and data providers across Australia. The AURIN Portal offers access to diverse data from multiple sources and facilitates data integration and data interrogation using open-source e-research tools (AURIN, 2018).

Since the portal covers the databases of the Australian Bureau of Statistics (ABS), National Exposure Information System (NEXIS), and others, the statistics used in this study were mainly derived from this source. The National Exposure Information System (NEXIS) has a specific modelling (i.e. geo-science) capability designed to provide comprehensive and nationally consistent exposure information. NEXIS provides aggregated exposure information for residential, commercial, and industrial buildings. Residential mobility data including the percentage of people living at the same address for five years and percentage people living at the same address for one year were obtained from the ABS database of 2011. The residential mobility variable included the percentage of people who had moved in the last five years and percentage of people who had moved in the last year and was downloaded from the National Exposure Information System (NEXIS) 2014.

Spatial databases are extracted from the portal at statistical area (SA) level 1. Statistical Area Level 1 is built from a whole Mesh Block (ABS, 2011). They have been designed by the ABS as the smallest area of output for the census of population and housing. In some cases, statistical area level 1 is also used to approximate a number of administrative regions for which census data are produced such as postal areas and state suburbs. Unlike traditional collection districts, statistical area level 1 more closely aligns with gazetted suburbs and localities.

Data for type of tenure includes percentages of owner-occupier dwellings, publicly rented dwellings and privately rented dwellings and was derived from National Exposure Information System (NEXIS). The variable of type of dwelling includes number of separate houses, semi-detached houses, two-storey houses, three-storey houses, and four or more storey houses was also derived from the NEXIS database.

The English proficiency variable was derived from the 2011 ABS database. The variable includes only the percentage of people with limited English proficiency. The residential density variable consists of the total number of dwellings per square kilometre and was obtained by calculating data of total dwelling downloaded from NEXIS and area of statistical area level 1 derived from the ABS database. Table 4-1 summarises the predictor variables used in this study.

Table 4-1: Summary of predictor variables

Variables	Measures	Source
Residential mobility	- Percentage of people living at the same address for five years - Percentage of people living at the same address for one year - Percentage of people who moved in the last five years - Percentage of people who moved in the last one year	- National Exposure Information System (NEXIS) 2014 - Australian Bureau of Statistics (ABS) 2011
Type of tenure	- Percentage of own dwellings - Percentage of rented dwelling publicly - Percentage of rented dwelling privately	- National Exposure Information System (NEXIS) 2014
English proficiency	- Percentage of people with limited English proficiency	- Australian Bureau of Statistics (ABS) 2011
Residential density	- Number of total dwellings/km2	- Australian Bureau of Statistics (ABS) 2011
Type of dwelling	- Number of separate houses - Number of semi-detached houses - Number of two-storey houses - Number of three-storey houses - Number of houses with four or more storeys	- National Exposure Information System (NEXIS) 2014

4.3.3. Derived data

Fire incident data are stored as points with x and y coordinates. This required converting the address location of the fire to a point on a map. Fire data are mapped by a process called geocoding. Geocoding involves interpreting an address location and if this process is successful, the result is usually a location expressed in Cartesian coordinates (x and y). These coordinates are then used to locate the fire in relation to other spatial data sets being mapped.

Geocoded fire locations can be viewed individually, as a group of dots with other fire events, or can be aggregated to polygons. By using a point-in-polygon counting process, the number of fires occurring within a fire agency's boundary can be calculated simply by the number of points that fall within that boundary area. ArcGIS is used to transform the data set into GIS. Figure 4-1 illustrates the distribution of fire incident across Melbourne Metropolitan region after geocoding process using ArcGIS.

Figure 4-1: Residential fire distribution across Melbourne region, year to year (2005 – 2015)

The model was designed and developed by means of a spatial grid-cells approach. The study area was divided into a finite number of equally-sized grid cells, each of which had a unique entity. The advantage of the grid approach is that it provides computational convenience especially when processing a large dataset. However, choosing the size of a grid cell is problematic. For example, the selection of a smaller size cell could lead to a higher number of zero observation cells, while a large cell size could lose the details of the embedded spatial heterogeneity in the phenomenon of interest.

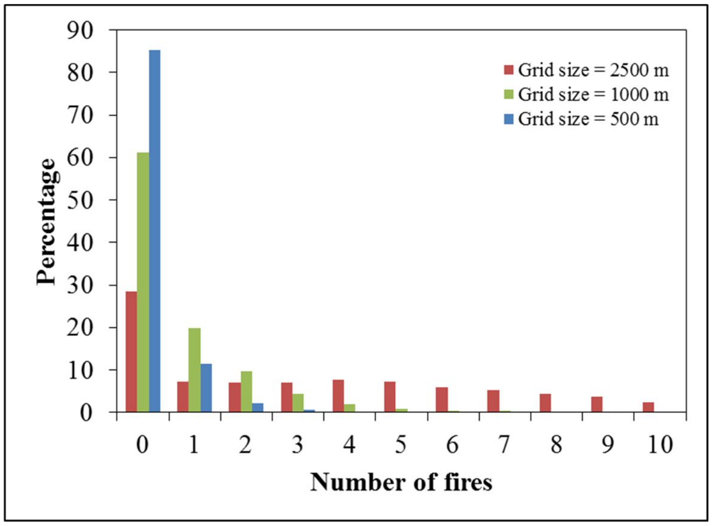


Figure 4-2: Distribution of zero values within grid cells across the study area

Figure 4-2 illustrates the distribution of zero values. For 2.5 x 2.5 km grid cells, about 28 per cent (849 out of 2,982) of the grid cells contained zero values, whilst for 1 x 1 km sized grid cells, 61 per cent contained zeros. The zero value indicates, first, that there was no fire incident within a cell during the period of study (i.e. April 2006 to May 2015) and, secondly, this is partly because of land use zoning with land parcels allocated to non-residential purposes such as industrial/commercial activities or parks and reserves. In order to determine the number of zero values across the grid cells, this study used 2.5 x 2.5 km sized grid cells for the modelling resolutions.

Not only fire data, but also the census data were recorded in an aggregated form as a square grid independent from the administrative boundaries of Statistical Area (SA) level 1. The incident records were associated with the attributes of the census grid cell into which they fell. MATLAB is used to complete an aggregation process. Like other statistical software packages, MATLAB enables for the fast and efficient processing for large datasets using a variety of analytical techniques.

4.4. MARKOV CHAIN MODEL

Defining residential fire risk in terms of probability cannot adequately address the complexity of fire risk. A better understanding of space and time in the context of fire risk can answer the complex questions regarding the way that fire risk behaves in space and time. The complexity of the local learning process and the ability of residents to retain and recall information about past fires can be used to explain fire risk from a different perspective. It is argued that fires in the immediate past tend to have a profound effect on the perception of present and future fire risk.

This research used the Markov chain model to estimate the likelihood of residential fire occurrence by considering the spatial and temporal dependence of fire risk. A detailed description of the method is given below.

4.4.1. Spatial and temporal models

To capture space and time in data modelling, numerous models have been developed including: (i) a spatial model which allows for spatial dependence (Hudson, 1969), (ii) a temporal model which takes into account the temporal behaviour of the diffusion process (Haynes et al., 1977, Hudson, 1971), and (ii) spatio-temporal models that consider space and time dependence (Hagerstrand, 1968, Usher and Williamson, 1970). Initially, Hagerstrand (1968) introduced a diffusion model with a stochastic mechanism to capture spatial interaction over time. The model is used to simulate a spatial diffusion process transmitted over time. It is based on an object requiring diffusion which spreads out from propagation sites to potential receivers as well as through interaction mechanisms between transmitters and receivers. The model also demonstrates the nearest effect or propensity to interact and exchange information, especially with individuals living in close proximity to one another.

Olsson (1969) suggested that in the Hagerstrand model, the spatial diffusion processes are governed by the flow of interpersonal information. Hagerstrand constructed the model by initially defining the notion of Mean Information Field (MIF). This is a matrix with cell values representing the likelihood that cells may receive a diffusion phenomenon from source cells such that the MIF represents how cells are related, in that information can flow between all of them (see Figure 4-3). Gale (1972) argued that the modelling of the innovation diffusion process by Hagertsrand is generally based on probability function that describes growth of population in space with limited resources (potential adopters) and on basic principles of spatial interaction (effect of mass, distance, barriers, etc.), with process time divided into discrete units.

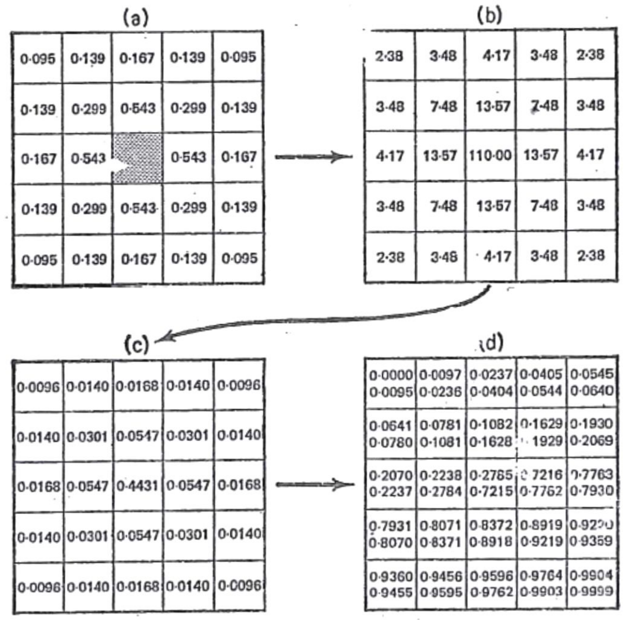


Figure 4-3: Example of the Hargerstrand's Mean Information Field (Haynes et al., 1977)

Nevertheless, some models have been developed which are similar to Hagerstrand's formal model of spatial and temporal interaction. For instance, Bailey (1968) developed a model of birth, death, and migration processes for a spatially distributed population. His model directly analyses a similar class of problem to that addressed by Hagerstrand's model. Bailey intended to provide a general accounting-type of notation, analogous to the classical diffusion equation. However, on the surface, the respective approaches of Bailey and Hagerstrand appear quite dissimilar (Gale, 1972). Bailey stresses an analytical formulation and the solution of stochastic differential equation systems, while Hagerstrand employs a mean information field as the basis for Monte Carlo simulations. Usher and Williamson (1970) developed an approach to examine demographic process from a deterministic perspective. Their finite-dimensional matrix is similar to Bailey's set of stochastic differential equations.

Similar to the Hagerstrand model, Brown (1970) and Allen (1982) proposed the Markov chain as a spatial and temporal dependence modelling technique in movement and diffusion research. The Markov chain model was based on the transition probabilities matrix, which refers to a set of transition probabilities from one step to another step. By adjusting the spatial order property, the transition matrix could be regarded as structurally isomorphic to Hagerstrands' mean information field (Gale 1972). Hence, Hagerstrand's conceptualization of the transition process of spatial interaction is a kind of Markov process model.

Table 4-2 shows a summary of several spatial and temporal models used to capture the space and time context of the event, together with their advantages and disadvantages. Compared to other spatial and temporal modelling methods, Markov modelling offers certain advantages. The main advantage lies in its great flexibility in expressing the dynamics of system behaviour. Markov models can model most kinds of system behaviours that a combinatorial model can. In addition, the Markov chain is an appropriate model that can model in a natural way a sequence-dependent behaviour. Sequence-dependent behaviour is behaviour that depends on the sequence in which certain events occur. One example is disaster risk perception behaviour where behaviour differs depending on whether one event influences the next event. However, Markov modelling techniques do have some limitations which make them inappropriate for some modelling situations. The two most important limitations involve state space size and model construction. A realistic model of a state-of-the art system can require a very large number of states. Solving models with so many states can challenge the computational resources of memory and execution time offered by computers that are currently widely available. The problem of correctly specifying states and inter-state transition is also generally difficult and awkward. This is especially so if the model is very large. It may be very difficult to construct a model of a large system and verify its accuracy.

Recall that the Markov property assumption is restrictive and may not be appropriate for many systems. If this is the case for an individual system, then Markov modelling is not an appropriate modelling technique for that system because any dependability estimate obtained from evaluating the model will not be meaningful. The more sophisticated Markov models can express much more complex system behaviour than the simplest one. However, they require more complex solution techniques that require more execution time. Consequently, currently, it is feasible to solve only simple Markov models of the more complex types. Finally, the form of the Markov model (states and transition) often does not have much of a physical correspondence with the system's physical or logical organization. This may make it comparatively difficult to obtain a quick intuitive visual interpretation of a model's evaluation in the same way as may be done with, for example, a digraph.

Table 4-2: Comparisons of Markov chain model and other spatial-temporal models

Spatial diffusion model	Approach	Space and time characteristics	Advantages	Limitations
Hagerstrand's model	Probabilistic	Mean Information Field	- Considers the nearest effect or propensity to interact and exchange information especially with individuals living geographically close - Based on Monte Carlo simulation	- The treatment of growth (i.e. the addition of adopters) and attrition is implicit in the simulation scheme. - Focused on physical diffusion, however many processes of the diffusion type are not pure. They are caused by interaction and transformations (Haynes et al., 1977) - The Hagerstrand diffusion processes are secondary and contingent events (Blaut, 1977) .
Bailey's model – birth, death, and migration process	Deterministic	Matrix of stochastic differential equation	- Considers a population with a possibly infinite number of sub-populations (Gale, 1972) - The growth and decline (i.e. entrance to and attrition from the system) is treated as part of general process	- The variances are more difficult to derive and solutions are available only for a limited number of cases (Gale, 1972) .
Usher and Williamson model – birth, death, and migration process	Deterministic	Finite-dimensional matrix of stochastic differential equation	- Working with finite number of subpopulations (Gale, 1972) - The growth and decline (i.e. entrance to and attrition from the system) is treated as part of general process	- Working with a finite number of subpopulations would in any case be worth investigation since all population of organism in the real world must be finite in extent (Gale, 1972).
Markov process	Probabilistic	Transition probability matrix	- Considers neighbourhood effect - A quite simple model of transition processes (Gale, 1972) - Time dependency (i.e. consider linked events whereby what happens next depends on the current state of the system) - Sequential event	- Focuses only on transition process (Gale, 1972) - Can require a large number of states - Model can be difficult to construct and validate - Model types of greatest complexity require solution techniques that are currently feasible only for small models

Spatial diffusion model	**Approach**	**Space and time characteristics**	**Advantages**	**Limitations**
				- Model is often not structurally similar to the physical or logical organization of the system
The macro model	Deterministic	- One-parameter logistics function - The Bass model	- Incorporate the percentages of adopters at each time point to make better estimate of the growth attributable to personal network persuasion (Valente, 1996) - Can be used to forecast expected levels of diffusion, rate of diffusion, external influence or innovativeness, and internal influence (i.e. interpersonal persuasion) (Valente, 1996) - It provides a parsimonious and analytical tractable way to look the whole system (i.e. market) and interpret its behaviour (Kiesling et al., 2012) - Fits many historic data on completed diffusion processes well (Kiesling et al., 2012)	- Interpretation of estimates is highly dependent on the time scale used to measure diffusion (Valente, 1996) - Do not measure whether people who are connected to one another engage in the same behaviour. Geographers have devoted considerable attention to trying to determine whether innovation spread between contiguous areas (Valente, 1996) - Require the assumption that the potential adopter population is homogeneous (Kiesling et al., 2012) - It is not possible to distinguish effect of different social processes on diffusion (Kiesling et al., 2012)
Network models	Deterministic	Network exposure	- Capture network influence - Can compare different network weighting mechanisms (e.g. relational, positional, centrality) in order to model and compare different social influence processes (Valente, 1996) - Simulation assumption regarding influences on adoption can easily be changed to achieve different outcomes (Valente, 1996)	- Rely on data which often difficult to collect data over a time period long enough for diffusion to occur (Valente, 1996). - Collecting complete network data is difficult (Valente, 1996)

4.4.2. Basic concept of stochastic process

As a formal definition, a stochastic process is a set of random variables $\{\mathrm{Z(t)}, \mathrm{t} \in \mathrm{T}\}$ defined in a given probability space. It is indexed by t, an element of index set T. The index set T is often represented in time so that $\mathrm{Z(t)}$ refers to a stochastic process in time t. Pinsky (2011) defined the stochastic process as a family of random variables $\{\mathrm{Z(t)}, \mathrm{t} \in \mathrm{T}\}$ defined in probability space of $(\Omega, \mathcal{A}, \mathrm{P})$. More formal definitions of stochastic process can be found in a number of studies (Bai and Wang, 2011, Billingsley, 1961, Ching and Ng, 2006, Çinlar, 2011, Blanco Castañeda et al., 2012, Iosifescu et al., 2010, Pinsky, 2011).

There are two fundamental characteristics of the stochastic process:

- State space, S, is defined as a set of all possible values of $Z(t)$. The range of $Z(t)$ generates a state space S which can be a discrete set (i.e. a set of non-negative integer number), or a continuous set (i.e. a set of real number). If state space S is discrete, the process refers to a discrete stochastic process; otherwise, the process is known as a continuous stochastic process if state space S is a continuous set. In this study, the state space S is defined as a binary set containing 'no fire' state (coded by 0) representing the situation where there has been no fire event and 'fire' state (coded by 1) representing the situation where at least one fire has occurred at a particular location.

- Parameter space (often called as index set or index of parameter), T, is defined as an ordered index set (usually interpreted as time). The parameter space may be discrete or continuous. In the case of a discrete index, the parameter space T can be regarded as $T = \{0,1,2,\cdots\}$ and in the case of the continuous, the parameter space T can be an interval $T = [0, \infty)$. However, in practice, observations might occur not only in time but also often depend on location such that parameter space T then refers to variables which have been ordered by locations. For instance, let D stand for the parameter space of location (space), and then random variable Z_s can be interpreted as process in location s (note that the brackets are used for time index and subscript for location). Studies related to $\{Z_s, s \in D\}$ with D is a set of locations, have been widely done by using earth dataset or GIS and the analysis is often known as geo-statistics analysis. Furthermore, some studies might combine both index sets into a set of pairs of time and location, denoted as (s, t), where s is an element of the index set of locations, D, and t is element of index set of time, T. Therefore a stochastic process is defined for two index sets, time and location, and rewritten as $\{Z(s,t), s \in D, t \in T\}$ or $\{Z_s(t), s \in D, t \in T\}$.

4.4.2.1. Time series process

A stochastic process $\{Z(t), t \in T\}$ with T as time is known as a time series process. The time series process $\{Z(t), t \in T\}$, first introduced by Box and Jenkins (1970), is defined as a set of random variables generated in a time sequence that is either discrete (e.g. in day, week, month, year) or continuous (e.g. time interval $[0, t]$). The formal definition of the time series process is as follows:

Definition 1 (Time series process):

For stochastic process $\{Z(\omega, t), \omega \in \Omega, t \in T\}$ *with* Ω *is probability space and* T *is index set (time), if*

i. t *constant,* $Z(\omega, t)$ *is random variable in* Ω.

ii. ω *constant,* $Z(\omega, t) = Z(t)$ *in* T *and* $Z(t)$ *is function of sample or realization and* $\{Z(t), t \in T\}$ *is called as time series process.*

Thus, time series is a realization or function of a sample form of a stochastic process.

The time series process $\{Z(t), t = 0,1,2,\cdots\}$ has mean function, μ_t,, variance function, σ_t^2, covariance function between $Z(t_1)$ and $Z(t_2)$, $c(t_1, t_2)$, and correlation function between $Z(t_1)$ and $Z(t_2)$, $\rho(t_1, t_2)$, which are defined as follows:

$$\begin{gathered}\mu_t = E[Z(t)] \\ \sigma_t^2 = E[Z(t) - \mu_t] \\ c(t_1, t_2) = E[\big(Z(t_1) - \mu_{t_1}\big)\big(Z(t_2) - \mu_{t_2}\big)] \\ \rho(t_1, t_2) = \frac{c(t_1, t_2)}{\sigma_{t_1}\sigma_{t_2}}\end{gathered} \tag{1}$$

where σ_{t1} is standard deviation of proses at time t_1 and σ_{t2} is standard deviation of process at time t_2.

In practice, one may find that raw data have a seasonal effect or depend on another process, making it difficult to analyse and model the behaviour for further application. Therefore, the notion of ‘stationary’ is used as a tool to transform raw data so that it is stationary. Figure 4-4 illustrates a comparison between stationary and non-stationary time series.

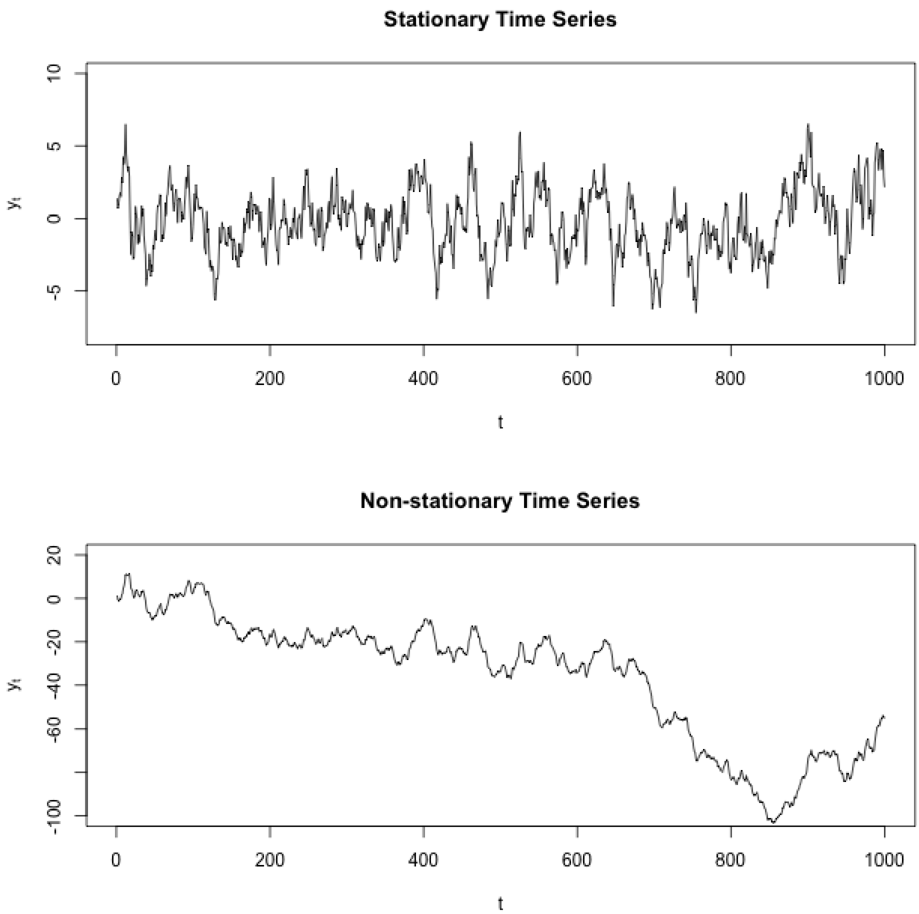


Figure 4-4: Illustration of stationary and non-stationary time series

Box and Jenkins (1970) pointed out that the stationary time series process is divided into two concepts: strictly stationary and weakly stationary (often known as second order of stationary). The process $\{Z(t)\}$ is called strictly stationary if joint distribution function of $Z(t_1), Z(t_2), \cdots, Z(t_n)$ and $Z(t_1 + u), Z(t_2 + u), \cdots, Z(t_n + u)$ are identical to each other $(t_1, t_2, \cdots, t_n)$ and $(t_1 + u, t_2 + u, \cdots, t_n + u)$ in index set T. On the other hand, weakly stationary can more easily be reached since it requires only the covariance function between $Z(t)$ and $Z(t + u)$ depends only on u (Box and Jenkins, 1970). In practice, weakly stationary is used more than strictly stationary because it is hard to determine the distribution function of the process. Formally, Box and Jenkins (1970) defined weakly stationary in a time series process as follows:

Definition 2 (Weakly stationary time series process):

A time series process $\{Z(t), t \in T\}$ *with index set* $Z = \{0,1,2,\cdots\}$ *is called stationer (second order, weakly stationary) if it satisfies:*

i. $E[Z(t)^2] = var\big(Z(t)\big) < \infty$ *for any* $t \in T$
ii. $E[Z(t)] = \mu$ *for any* $t \in T$
iii. $cov\big(Z(t), Z(t+u)\big) = E[(Z(t)-\mu)(Z(t+u)-\mu)] = c(u)$ *for any* $t, u \in T$,
iv. *or* $c(v,u) = c_Z(v+t, u+t)$ *for any* $v, u, t \in T$,

This definition implies that if $\{Z(t), t \in \mathrm{T}\}$ is stationary, then the auto-covariance function $c(v,u) = c_Z(v-u, 0)$ for any $v, u \in \mathrm{T}$. So that for the stationary process, auto-covariance function can be noted as a function of a variable which is $c(u) = c_Z(u,0) = cov(Z(t+u), Z(u))$ for any $t, u \in \mathrm{T}$. Autocorrelation function, for any $t, u \in \mathrm{T}$, can be noted as

$$\rho(u) = \rho_Z(u,0) = {c(u)}\big/{c(0)} = corr(Z(t+u), Z(u)).$$

The theory and details of the time series can be found in several literatures (Anděl, 1993, Bai and Wang, 2011, Bell, 2012, Box and Jenkins, 1970, Brockwell and Davis, 2013, Hamilton, 1994)

4.4.2.2. Spatial process

Apart from the time series, the spatial process is also a stochastic process. However, in practice, determining the index set of locations, D, is very difficult compared with the index set of time, T. Time can be sorted by its unit and can be described in one-dimensional space. Here, the forward and backward movement from the target point (null point) can be determined clearly in a time lag. In spatial process, determination the space lag is complex. It requires two main characteristics: distance and direction.

Furthermore, a spatial process can be defined as well as a time series process. A stochastic process $\{Z(\omega, s), \omega \in \Omega, s \in D\}$ or $\{Z_{\omega,s}, \omega \in \Omega, s \in D\}$ with ω fixed is known as a function of sample or realization. $\{Z_s, s \in D\}$ is spatial process for fixed $D \subseteq \boldsymbol{R}^2$, two dimensions of Euclidean space (Gelfand et al., 2010). Formally, the spatial process is defined as follows:

Definition 3 (Spatial process):

For the stochastic process $\{Z_{\omega,s}, \omega \in \Omega, s \in D\}$ *with* Ω *is probability space and* D *is index set (space), if*

i. s *constant,* $Z_{\omega,s}$ *is random variable in* Ω.

ii. ω *constant,* $Z_{\omega,s} = Z_s$ *in* D *and* Z_s *is function of sample or realization and* $\{Z_s, s \in D\}$ *is called as spatial process.*

Similar to the time series process, the variables are considered stationary if the distribution of the random variable is invariant to translation. In other words, for any shift h, the distribution of $Z_{s_1}, Z_{s_2}, \cdots, Z_{s_n}$ and $Z_{s_1+h}, Z_{s_2+h}, \cdots, Z_{s_n+h}$ is identical for each $s_1, s_2, \cdots, s_n$ and $s_1 + h, s_2 + h, \cdots, s_n + h$ in index set D. This phenomenon is known as strictly stationary. However, in practical terms, to have all moments being invariant to translation is difficult because of observation limitations. Hence, it is sufficient for the stationary of the process to consider that the first moments (mean and covariance) are constant. This is known as second order stationary or weakly stationary. Formally, second order stationary (weakly stationary) of the spatial process is defined as follows:

Definition 4 (Second order stationary in spatial process):

A spatial process $\{Z_s, s \in D\}$ *with* $D \subseteq R^2$ *is called second order stationary if satisfies:*

i. $E[Z_s] = \mu$, *for any* $s \in D$

ii. $cov(Z_s, Z_{s+h}) = c(s, s+h) = c(h)$ *for any* $s, h \in D$

In other words, the second order stationary of the spatial process is satisfied if the means of Z_s and $cov(Z_s, Z_{s+h})$ are constant for any $s \in D$. Hence, the covariance depends only on lag of vector h not on point s. For two locations, auto-covariance (often called as covariogram) can be written as

$$cov(Z_{s_1}, Z_{s_2}) = E[(Z_{s_1} - \mu)(Z_{s_2} - \mu)] = c(s_1 - s_2), \text{ for any } s_1, s_2 \in D \qquad (2)$$

If $s_1 - s_2 = h$, Equation (2) can be noted by $\mathrm{c}(\mathrm{s}_1 - \mathrm{s}_2) = \mathrm{c}(\mathrm{h}) = \mathrm{c}(|\mathrm{h}|, \varphi)$ where φ is angle between x and vector h and $|\mathrm{h}|$ is length of vector h. Length of vector can be determined by using the Euclidean distance of two points formulation: $\sqrt{(\mathrm{x}_1 - \mathrm{x}_2)^2 + (\mathrm{y}_1 - \mathrm{y}_2)^2}$, where $(\mathrm{x}_1, \mathrm{y}_1)$ and $(\mathrm{x}_2, \mathrm{y}_2)$ be the location of point s_1 and s_2, respectively. The stationary of the spatial process is an isotropic process which is the covariance depending on direction and distance. If φ is ignored such that $cov(Z_{s_1}, Z_{s_2})$ depends only on distance, then the spatial process $\{Z_s, s \in D\}$ is known as stationary isotropic.

The theory and details of the spatial process can be found in several literatures (Ayala et al., 2006, Cressie, 2015, Diggle, 2014, Gelfand et al., 2010)

4.4.3. Markov chain

Given that n space represents the area of interest, the occurrence of a residential fire in a grid cell $(\mathrm{s} = 1, \cdots, \mathrm{n})$, on a random spatial and temporal process, can be formally defined as a set of discrete random processes $\{\mathrm{Z}(\mathrm{s}, \mathrm{t})\}$or $\{\mathrm{Z}_\mathrm{s}(\mathrm{t})\}$ in a given probability space and indexed by t, $\mathrm{t} = 1, \cdots, \mathrm{T}$.

The set of values of $\mathrm{Z}_\mathrm{s}(\mathrm{t})$ is the state space Ω of the random process. It might be a finite state space or countably-infinite state space. This study used a Markov chain with finite state space: a two-state Markov chain and a three-state Markov chain. For the two-state Markov chain, the state space Ω is defined as a set containing a 'no fire' state where there has been no fire event and a 'fire' state where at least one fire has occurred within the designated neighbourhood. The number of fires that have occurred in the past within a neighbourhood also affects fire risk, which is modelled using the three-state Markov chain. A three-state Markov chain represents state space containing the states of 'no fire', 'a single fire, and 'two and more fires.

Suppose, $\{\mathrm{Z}(\mathrm{s}, \mathrm{t})\}$indicates the presence of a residential fire at a location s, $\mathrm{s} = 1, \cdots, \mathrm{n}$, at a time t, $\mathrm{t} = 1, \cdots, \mathrm{T}$, so that the vector $\mathbf{Z}(\mathrm{t}) = (\mathrm{Z}_1(\mathrm{t}), \cdots, \mathrm{Z}_\mathrm{n}(\mathrm{t}))'$ represents a map describing the presence of a fire at time t. By assuming the fire occurrence sequence captured through a stochastic process model for $\mathbf{Z}(\mathrm{t})$ which follows a first-order Markov Chain, the conditional probability is then defined as $\mathrm{P}(\mathbf{Z}(\mathrm{t}+1) | \mathbf{Z}(\mathrm{t}), \cdots, \mathbf{Z}(1)) = \mathrm{P}(\mathbf{Z}(\mathrm{t}+1) | \mathbf{Z}(\mathrm{t}))$. It is the probability that a fire occurring at time $\mathrm{t}+1$ given historical fire incidents, (i.e. $\mathbf{Z}(\mathrm{t}), \cdots, \mathbf{Z}(1)$) depends only on fire incidents that occurred at time t. Moreover, the Markov chain model can be simplified by assuming conditional independence across regions, so that

$$P(\mathbf{Z}(t+1)|\mathbf{Z}(t)) = \prod_{s=1}^{n} P(Z_s(t+1)|\mathbf{Z}(t)) \tag{3}$$

In other words, the probability in Equation (3) denotes that given the states (fire or no fire) at a location s, the probability distribution of where the fire occurrence state changes to the next state, i.e. $Z_s(t+1)$ depends only on the presence of fire $Z(t)$.

4.4.3.1. The one-step transition probability

The probability on the right-hand side of Equation (3) for any $s = 1, \cdots, n$ and for all $i, j \in \Omega$, is known as a one-step transition probability that can be written as follows:

$$P(Z_s(t+1) = j|Z(t) = i) = p(s,t) \tag{4}$$

This is the probability of fire occurrence at a location s at time t given the occurrence of a fire event within its neighbourhood at time $t-1$. If one-step transition probabilities $p(s,t)$ are independent of t, a Markov Chain is called as a stationary Markov chain $p(s,t) = p_{ij}(s)$. In other words, the probability of moving from one state to another state is not influenced by the time at which the transition takes place. The one-step transition probability, $p_{ij}(s)$ is often arranged in a matrix. This is known as the one-step transition probability matrix, denoting $\mathbf{P}(s)$ as follows:

$$\mathbf{P}(s) = \begin{bmatrix} p_{11}(s) & p_{12}(s) & \cdots & p_{1k}(s) \\ p_{21}(s) & p_{22}(s) & & p_{2k}(s) \\ \vdots & & & \vdots \\ p_{k1}(s) & p_{k2}(s) & \cdots & p_{kk}(s) \end{bmatrix} \tag{5}$$

where k represents the number of states (e.g. $k = 2$ represents a two-state Markov chain and $k = 3$ represent a three-state Markov chain). A transition probability matrix has several features: it is a square matrix since all possible states must be used in both k row and k column. The transition matrix entries are between 0 and 1, inclusive; this is because all entries represent probability. The specific feature of a transition probability matrix is that the sum of the entries in any row is equal to 1. This is because the numbers in the row give the probability of change from one state to another state.

The maximum likelihood estimation (MLE) for $p_{ij}(s)$ for any $s = 1, \cdots, n$ and for all $i, j \in \Omega$ is

$$\hat{p}_{ij}(s) = \frac{n_{ij}(s)}{N_i(s)} \quad (6)$$

where $n_{ij}(s)$ stands for the number of transitions from state i to j at location s and $N_i(s)$ is the number of transitions from i at neighbourhood of s. In practice, the MLE method is applied as follows:

- count the frequency of states that satisfy $Z_s(t+1) = j \cap Z^*{}_s(t) = i$ for $t = 1,2,\cdots,T$ with $Z^*{}_s(t)$ represents state within neighbourhood of location s;
- add these frequencies thus: $\sum_{t=1}^{T} Z_s(t+1) = j \cap Z^*{}_s(t) = i$;
- repeat these steps for all states in S other than i and add all these frequencies to obtain the total number of one-step fire occurrences starting in i;
- divide the number from the second and third step in order to obtain the probability.

For the two-state Markov chain illustration, let Z_{1503} is a residential fire sequence at grid cell #1503 (a cell located in Melbourne's Inner East region). The transition probability of current states is fire given that the previous state is no fire (i.e. denoted as p_{01}) and is then calculated by summing the frequencies of $Z_{1503}(t+1) = 1 \cap Z^*{}_{1503}(t) = 0$ and dividing by the total frequencies of the process coming from the 'no fire' state (i.e. $Z^*{}_s(t) = 0$),

$$\hat{p}_{01} = \frac{39}{104} = 0.375$$

The result above indicates that the probability of fire occurrence at grid cell #1503 is equal to 0.375 if there was no fire incident in the last one month within its neighbouring grid cells. Similarly, we obtain results of 0.625, 0.857, and 0.143 for $\hat{p}_{00}$, $\hat{p}_{10}$, and $\hat{p}_{11}$ respectively; the result can be written in a matrix as follows:

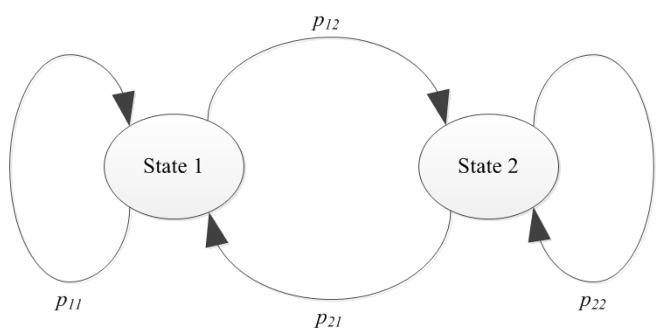
$$\hat{\mathbf{P}}(1503) = \begin{pmatrix} 0.625 & 0.375 \\ 0.857 & 0.143 \end{pmatrix}$$

By repeating the procedure, transition probabilities across the study area are then estimated.

The transition matrix entries are between 0 and 1 inclusive because all entries represent probability. The specific feature of a transition probability matrix is that the sum of the entries in any row is equal to 1. This is because the numbers in the row have the probability of changing from state to another state. The same condition must be fulfilled: $0 \le p_{ij}(s) \le 1$, for $i, j \in S$ and $s \in D$

$$\sum_{k=1}^{m} p_{ik} = \sum_{k=1}^{m} P(Z(t+1) = k | Z(t) = i)$$
$$= 1$$

If $p_{ij}(s) = 1$, the state i is said to be an absorbing state; meaning that if the process enters this state, it cannot leave it.



$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

Figure 4-5: A two-state Markov Chain in which each state is accessible. The transition probability matrix **P** with entries p_{ij} represent the probability at which transition is made from state *i* to state *j*

A Markov chain is usually shown by a state transition diagram. Figure 4-5 illustrates a two-state Markov Chain. Here, there are just two different states (occurrence of a fire and no fire), and there are four possible transitions. The fire status can move from state 1 to state 2, and vice versa. It is also possible to make a transition within the state, from state 1 to state 1, or from state 2 to state 2. This type of Markov model is often known as an irreducible Markov Chain whereby each state of the Markov Chain can be accessed from other states. The term p_{12} corresponds to the probability of a transition process from state 1 to 2. In addition to the characteristic of the transition probability matrix where the sum of the row is equal to one, the concentration of probability along the main diagonal of the matrix indicates a high tendency for chronological persistence of Markov Chain. This means that when the process enters a state, it tends to remain in the same state rather than move to others.

4.4.3.2. The k-step transition probability

The one-step transition probability as described earlier is the probability of transitioning from one state to another in a single step. However, one might be interested in estimating the probability of transitioning from one state to another in more than one step. The k-step transition probability of a Markov Chain is the probability that the process goes from state i to j in k transitions or steps. In this study, one step is delineated by one month. Thus, time step is referred as a monthly basis.

$$p_{ij}(s)^{(k)} = P(Z_s(t+k) = j|Z(t) = i) \tag{7}$$

and the associated m-step transition matrix is

$$P(s)^{(k)} = \{p_{ij}(s)^{(k)}\} = P^k, \text{ for } k = 1,2,\cdots \tag{8}$$

When steps become larger (k becomes large), the probability in the transition process, both into and out of a state, is likely to be at a steady state. This is often referred to as a 'state of equilibrium'. In the case of fire, the equilibrium state occurs when the number of residential fires in an area remains relatively steady over a period of time. In contrast, some areas might experience significant fluctuations in the distribution of fire with extreme high and low values. In this paper, we calculated the k-step transition in order to examine the month-to-month probability of fire occurrence.

4.4.3.3. Residential fire risk spatial modelling

Space and time play a vital role in the propagation of information. Space shapes the way that information spreads from one person to another, while time involves the moment at which the information is generated to the point at which it is accepted or rejected, and the subsequent response. This research applied this knowledge to capture the space and time dimensions in the risk information propagation process which in theory, affects local learning and the 'memoryless' effect.

Spatial temporal relationships were established by demarcating neighbourhoods for each of the cells across the grid. As shown in Figure 2, a neighbourhood is delineated by identifying cells, which are spatially adjacent to the scanning cell. Thus, the neighbours – that is a set of eight cells surrounding it – are referred as the 'neighbourhood in space'. Neighbourhood operation was implemented across a raster grid, one cell at a time. As each cell, a new value is computed as a function of its scanning neighbourhood. The neighbourhood function is then extended into time to create the 'neighbourhood in space and time' (see Figure 2). The size is similar to what most residents of an area might commonly perceive to be their neighbourhood within which they access vital infrastructure and amenities such as train stations, shopping centres and entertainment. This neighbourhood operation is then temporally integrated to scan the presence or absence of a fire or more within the time threshold of a month.

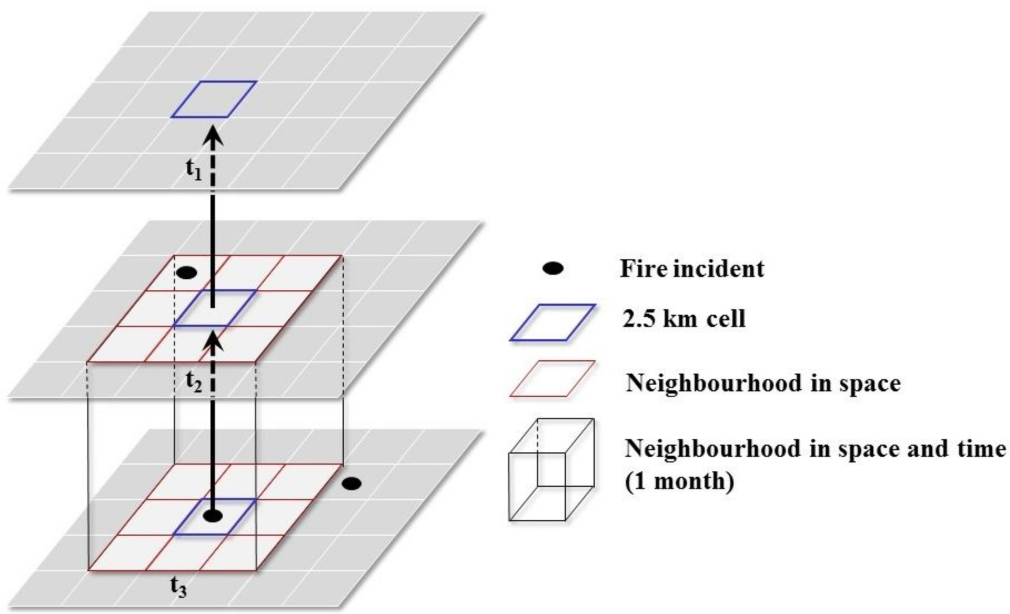


Figure 4-6: Neighbourhood in space and time

On the other hand, time lag is defined as a period between fire occurrences expressed as a discrete unit (i.e. monthly). Hence, time is viewed as a set of discrete variables which values of variables are viewed as occurring at distinct, separate "points in time" or are viewed as being unchanged throughout a particular period of time. The discrete time often corresponds to a clock or calendar that gives a fixed reading of certain timestamp (e.g. 2.30, January 2018, 3 January 2017) for a while and then jumps to a new fixed reading of 2.31, February 2018, or 4 January

2017, and so on. In this framework, each fire occurrence or set of fire occurrence is measured once at each time period.

To manage spatial data which is changing over time, combining the space and time dimensions into one map is an alternate technique. Space and time, thus, respectively coincide with horizontal and vertical planes. The location of fire incidents not only changes over the plane but is also tracked by time. When a fire occurs from one location to another, a sloping line indicates the distance takes time. Moreover, the distribution of fire occurrence can be easily analysed across space over time. Figure 4-7 illustrates how the distribution of fire occurrence changes over time either as a point which is moving from one location to another location over time or as a region (i.e. cluster) which is moving and shrinking.

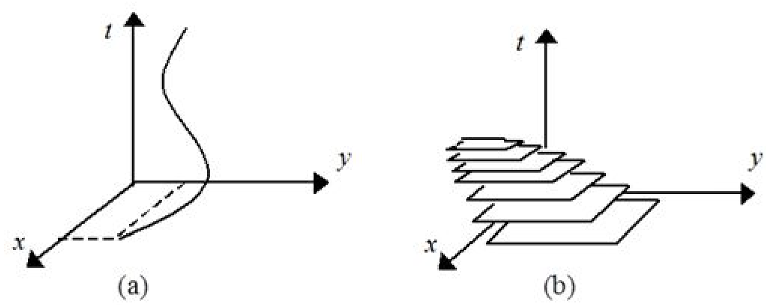


Figure 4-7: Illustration of the distribution of fire incidents over time and space

As a synthesis of the construction of the space and time dimension, Figure 4-8 illustrates the interaction between fire, time and space in a three-dimensional frame. In space, when a fire occurs in an area, the information about the fire occurrence is first transmitted to the immediate neighbourhood and then communicated across a larger region. Since the scale of information spread diminishes with distance, only those fire incidents that occur within a certain threshold distance from location s (i.e. neighbourhood of s) would have more impact on residents in relative terms. Kadushin (2004) argued that distant objects or phenomena have limited effects; hence, the influence of the focal object on others beyond its neighbourhood is relatively small. With time, the information about fire and associated risk starts to diffuse over space but its intensity dissipates with time. Generally, individuals tend to remember and pay attention to events that have occurred in recent time. Hence, given that a residential fire occurred at time $\mathrm{t}-\mathrm{k}$ for $\mathrm{k}=1,2,\ldots$, only those residential fires that occurred at $\mathrm{t}-1$ potentially influence individuals' perceptions of fire risk. The Markov process then follows, which is the probability that a fire incident following on from another depends on the dimensions of space and time.

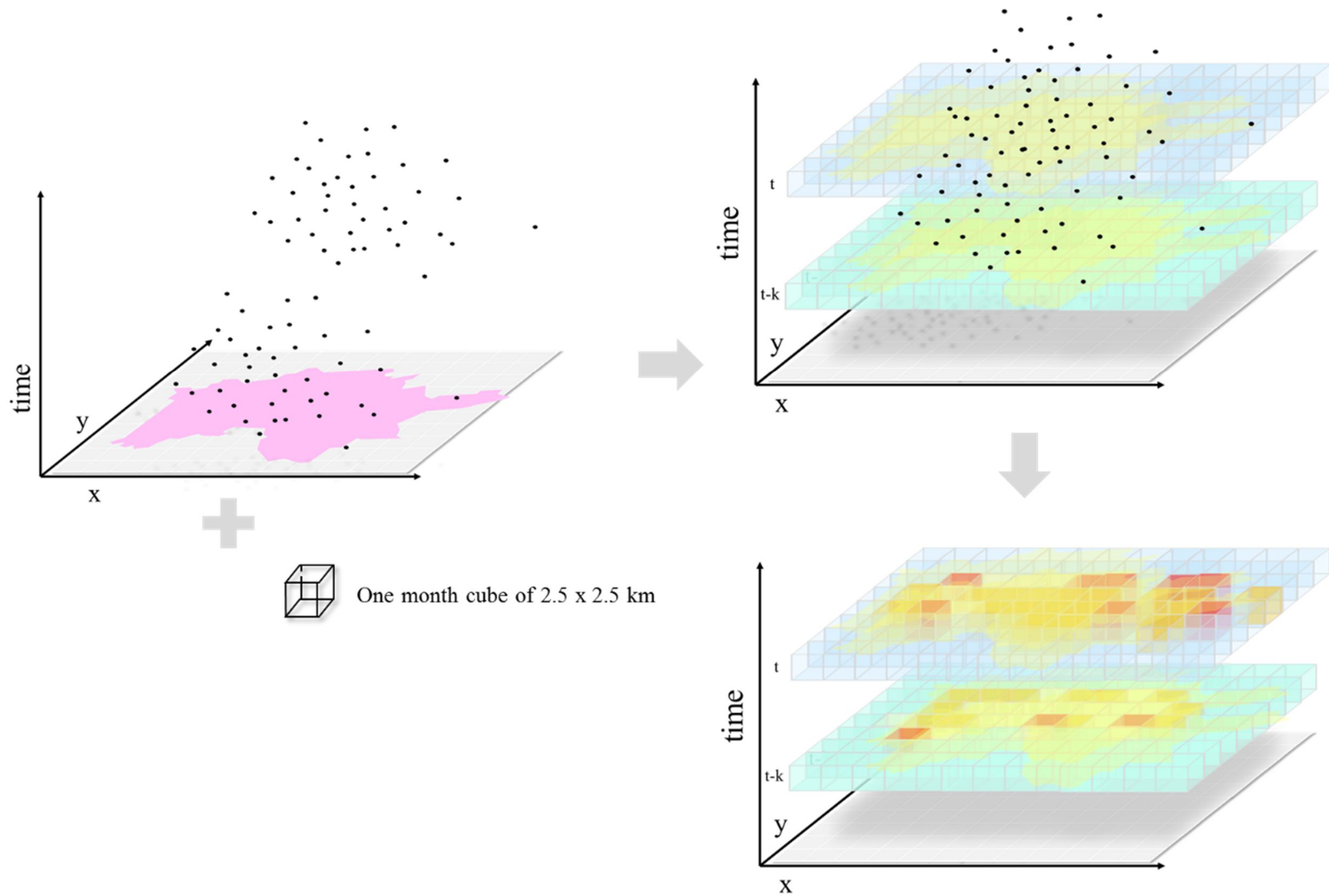


Figure 4-8: Spatial temporal framework for modelling fire risk as a stochastic process

When a fire occurs in a neighbourhood, the likelihood of fire occurrence within a certain distance and time is affected. This makes the phenomenon of fire both space- and time-dependent. Building on this stochastic approach with the spill-over effect over time and across space, the historical specificities of fire incidents at a particular time and at a specific location can be captured to improve the likelihood estimation.

4.5. GEOGRAPHICALLY WEIGHTED REGRESSION MODEL

As discussed earlier, the objective of this research is to identify key urban characteristics underpinning fire patterns over time and across space. Geographically Weighted Regression is used to identify the spatial drivers underpinning spatial patterns of fire risk. A detailed description of the method is presented below.

4.5.1. Spatial analysis

Spatial analysis is a method that employs locational information in order to produce a better understanding of the processes generating the experimental attribute values (Fotheringham et al., 2003). Hence, spatial analysis generates new information from spatial data. Fortin and Dale (2005) suggested that spatial analysis also attempts to determine a generation of spatial patterns through one or several processes.

Spatial analysis, however, differs from traditional or non-spatial analysis in two respects. Firstly, the traditional methods have been developed only for non-spatial data (Brunsdon et al., 1996). They are not appropriate for spatial data. Fortin and Dale (2005) argued that these traditional techniques have unique properties and problems which require different statistical methods and modelling approaches. The main issue is related to the location at which the model such as regression is undertaken. The model may differ over space in a different location (Fotheringham et al., 2003). Secondly, statistical analysis for spatial data has to deal with two types of potential local variation: the local relationship being measured in attribute space and the local relationship being measured in geographical space (Fortin and Dale, 2005). This means that spatial analysis involves attribute information as well as geographical information.

When analysis is conducted in the practical or real world, it is possible for the same input to produce different outcomes given that specific areas have unique characteristics such as the location, type of households, climate, and others. Consequently, this natural outcome cannot be explained by a simple global model. Fortin and Dale (2005) suggested that a global model tends to indicate the spatial pattern characteristics of the whole study area, while local statistics are expected to generate explicit differences in the patterns observed in various parts of the study area. Fotheringham et al. (2003) also highlighted that heterogeneous spatial data is not appropriate with a global model which works with homogenous data. Consequently, a global model often produces conclusions that are likely to be biased.

Table 4-3 summarises several differences between global and local models. Global models are typically single-valued while local model are multi-valued since different statistical value can occur in different locations (Brunsdon et al., 1996). Consequently, global models are non-mappable. They are GIS-unfriendly which means that they cannot be analysed with GIS tools. Conversely, local models are GIS-friendly. They can be mapped and examined within a GIS. Therefore, local models involve spatial statistics, whilst global statistics are spatially limited. Fotheringham et al. (2003) suggested that local model indicate the differences across space, whereas global model imply that a single value or some existing pattern can represent all parts of the study region. This demonstrates that local models are useful when searching for exceptions. This is known as 'local hot spots analysis'.

Table 4-3: Comparison of global and local model (Fotheringham et al., 2003)

Global	Local
- Summarise data for whole region	- Local disaggregation of global statistic
- Single-value statistics	- Multi-valued statistic
- Non-mappable	- Mappable
- GIS-unfriendly	- GIS-friendly
- Spatially limited	- Spatial
- Stresses similarities across space	- Stresses difference across space
- Searches for regularities or laws	- Searches for exceptions or local hot spots
- Example: ordinary least square model	- Example: GWR

There are two issues that cannot be ignored in studies on spatial modelling: spatial autocorrelation and heterogeneity. Cliff et al. (1995) explained spatial autocorrelation thus: "If the presence of some quantity in a sampling unit (e.g. a country) makes its presence in neighbouring sample unit (e.g. adjacent countries) more or less likely, we say that the phenomenon exhibits spatial autocorrelation". This explanation of autocorrelation is in line with Tobler's first law of geography. The law indicates that the association among the values of a given variable can be defined as a function of the spatial distances between them or their locations in space (Tobler, 1970). Therefore, the notion of spatial dependence indicates that there is an absence of independence between data from neighbouring locations (Fortin and Dale, 2005).

A number of statistical methods have been developed to assess the spatial autocorrelation of space data both globally and locally (Anselin, 1995, Ord and Getis, 1995). The most common is Moran's Index. Moran's Index is a test of spatial autocorrelation which has values ranging from -1 (indicating perfect dispersion) to +1 (indicating perfect correlation). A zero value indicates a random pattern (see Figure 4-9). The global Moran's Index is used to assess the spatial agglomeration degree of residential fire incidents and is formulated as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x}) z_j}{\sum_{i=1}^{n} (x_i - \bar{x})} \tag{9}$$

where n is the total number of samples, x_i is the number of fires in location of i, $\bar{x}$ is the mean value, w_{ij} is the spatial weight value, and S_0 is the sum of all its elements.

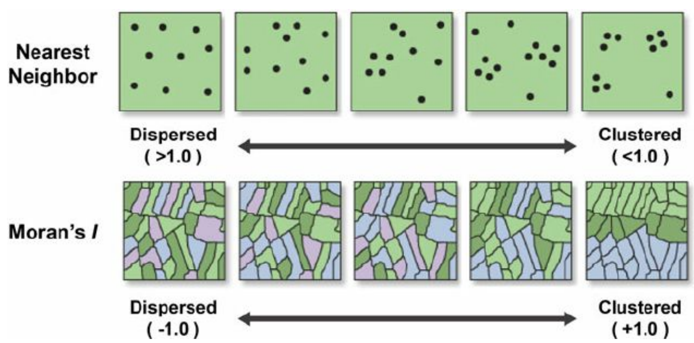


Figure 4-9: Spatial autocorrelation

Spatial heterogeneity refers to the irregular distribution of an event or relationship across a space (Anselin, 1988). Spatial heterogeneity is also defined as a structural variability in the form of systematically varying model parameters. It is often related to locations in space, missing variables, and functional misspecification.

There are several reasons why measurements of relationship are expected to vary over space. One of which is related to the sampling variation. Fotheringham et al. (2003) suggest that the sampling variation is uninteresting in that it is associated with a statistical artefact. It is not related to any causal spatial process. The second reason concerns the model's misspecification of reality. Anselin (1988) pointed out that the possibilty that one or more related covariate variables might be omitted from the model or be represented by an inappropriate functional form. Thus, to solve this problem, mapping local statistics is useful for clearly understanding the nature of model misspecification (Fotheringham et al., 2003). The last reason is that some relationships are essentially different across the study region; this is known as 'real heterogeneity' (Wheeler and Tiefelsdorf, 2005).

4.5.2. GWR and Ordinary Least Square model

The Geographically Weighted Regression (GWR) model was originally developed from the Ordinary Least Squares (OLS). It was further improved with the continuous development of statistical measures such as maximum likelihood estimation of the kernel bandwidths, spatial autocorrelation among the residuals and heterogeneity of the local model parameters (Wheeler and Tiefelsdorf, 2005). Parameters derived from the OLS model are usually applied as a global parameter across the space over which measurements are taken. However, often, the global parameter might not represent the actual situation. There might be a local variation over space to be accommodated. Hence, local variation requires local analysis rather than global analysis in order to capture the actual local reality. Therefore, the GWR model is an extended variation of the traditional OLS model which takes spatial heterogeneity into account by incorporating the spatial location of data.

Hanham and Spiker (2004) pointed out that GWR is based on three main principles: (i) spatial data are non-stationary, (ii) the spatial structure of data significantly influences the estimation of the relationships between variables, and (iii) the relationships between variables may be localized and varied across study region. Hanham and Spiker (2004) also stressed that the GWR model can capture local spatial variation. The common technique is to calibrate multiple regressions at each sampled point. In the GWR model, the regression fitting at each sample point is based on a spatial proximity approach used as a weighting function for an observation. This means that observations near the location at which estimation is assumed have more influence to the analysis than the distant observations.

4.5.3. Formal definition

A typical model used in geographical analysis is linear regression (often known as ordinary least square model). In this technique, the dependent variable is modelled as a linear function of a set of independent variables, as follows:

$$r(s) = \beta_0 + \sum_{k=1}^{n} \beta_k x_k(s) + \varepsilon(s) \tag{10}$$

where $r(s)$ is the observation at location s of dependent variable, $x_k(s)$ represents the observation at location s of the kth independent variable, and the $\varepsilon(s)$s are independent, normally-distributed error terms with zero means. The term β_k represents the coefficient associated with the kth independent variable. It is determined from a sample of n observations. To estimate the β_ks, the least squares method is typically used; using matrix notation, this may be expressed as follows:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^t\mathbf{X})^{-1}\mathbf{X}^t\mathbf{R} \tag{11}$$

where the independent observations are the columns of $\mathbf{X}$ and the dependent observations are the single column vector $\mathbf{R}$. The vector $\hat{\boldsymbol{\beta}}$ contains the coefficient estimates.

The Geographically Weighted Regression (GWR) is a multivariate regression that estimates the relationship between a dependent variable (i.e. fire risk) and independent variables (e.g. spatial characteristics) at the local level (Fotheringham et al., 2003). This technique can capture local variations because it produces a set of regression parameters for every location across the study area (area of interest). However, the global Ordinary Least Square (OLS) regression cannot capture this phenomenon because it assumes that the relationship between dependent and independent variables is constant across the study area.

GWR is a relatively simple technique that extends the traditional regression framework of equation (10) by allowing local variations in rates of change so that the coefficients in the model rather than being global estimates are specific to a location s. The regression equation is then:

$$r(s) = \beta_0(s) + \sum_{k=1}^{n} \beta_k(s) x_k(s) + \varepsilon(s) \tag{12}$$

where $\beta_k(s)$ represents the value of the kth parameter at location s. Note that equation (10) is a special case of (12) in which all of the coefficient estimates are constants across study region. As shown below, the point s at which estimates of the parameters are obtained is completely generalized and need not refer only to the points at which data are collected. With GWR, it is easy to compute parameter estimates of, for instance, any location lying between data points so that it will be possible to produce detailed maps of spatial variations in the relationships.

In this study, using the Markov Chain model, the probability of residential fire occurrence at location s is defined regardless of whether the starting state assumes that there have or have not been previous fires, $\pi_i(s)$ for $s = 1, \cdots, n$. Because the objective of this study was to examine the relationship between the probability of fire occurrence and a range of spatial indicators, difficulties might arise later with some predicted values of probability being less than zero or greater than one. To solve this problem, it was necessary to transform the probability, π_i. The logit transformation is used such that,

$$L(\pi_i(s)) = \ln\left(\frac{\pi_i(s)}{1-\pi_i(s)}\right)$$

This transformation maps the number of values ranging from zero to one onto the number range $-\infty$ to $+\infty$. This is insufficient for further statistical analysis so that, generally, the GWR model, for $s = 1, \cdots, n$, is specified as:

$$L(\pi_i(s)) = \beta_0(s) + \sum_{j=1}^{k} \beta_j(s)x_j(s) + \varepsilon(s) \tag{13}$$

where $x_j(s)$ represents the covariate variables associated with spatial characteristics, $\beta_j(s)$ are the parameter to be estimated, and $\varepsilon(s)$ is a random effect describing spatially unstructured variation which has the Normal Distribution with mean 0 and variance ${\sigma_s}^2$. The term s represents the vector coordinates of a particular location (i.e. longitude and latitude). This model allows for variation of the parameter estimates because it is likely to capture local effects.

It is noted that an important issue of GWR is its calibration. The calibration of the GWR function is needed for each independent variable X and at each location s. The common coefficient estimation technique is traditional weighted least squares regression, such as

$$\widehat{\boldsymbol{\beta}}(s) = [\mathbf{X}^T\mathbf{W}(s)\mathbf{X}]^{-1}\mathbf{X}^T\mathbf{W}(s)\mathbf{R} \tag{14}$$

where $\mathbf{W}(s)$ is an $n \times n$ diagonal matrix whose elements denote the geographical weighting of observation data for observation at location s. The weight matrix, $\mathbf{W}(s)$, is computed for each $s = 1, \cdots, n$ because the weight matrix in GWR represents the different degree of importance of each individual observation in the dataset; that is, it denotes the connectivity between observations. The closer the observation is to location s, the greater is the weight and vice versa. Each location has a unique weight matrix.

4.5.4. The spatial weights matrix W

The GWR model is used to estimate parameters in the presence of presumably interdependent variables. This requires an analysis process to define the type of interdependence and to examine the influence of one location on another. In practice, this is resolved by recognizing the connectivity between the locations in a $n \times n$ matrix. As mentioned in the section above, the matrix is described as a weight matrix of spatial connectivity matrix. This matrix defines a priori assumptions about the potential interaction between locations. The matrix also shows the effect of some locations upon a given location. Put simply, the weigh matrix identifies who is and who is not a neighbour.

Traditionally, there are two weighting regimes that can be used to define the connectivity between observations: fixed kernel and adaptive kernel. The fixed kernel assumes a fixed distance, but the number of nearest neighbours varies; while for the adaptive kernel, the distance varies, and the number of neighbours remains constant. The common fixed kernel is the Gaussian distance decay-based function defined as follows:

$$w_{s,j} = \exp\left(-\frac{d_{s,j}}{h^2}\right) \tag{15}$$

where $d_{s,j}$ is the Euclidean distance between location s and j and h is a non-negative parameter known as the bandwidth, indicating the influence of distance decay.

The limitation of the fixed kernel function is the availability of data points for model calibration. Some locations across the study area might have only a few data points available to calibrate the model. Hence, where there is this weak data problem, the calibration might appropriate only for the local model based on very few data points around the centre of location. Consequently, this may increase the standard error resulting in under-smoothed surfaces (see Figure 4-10).

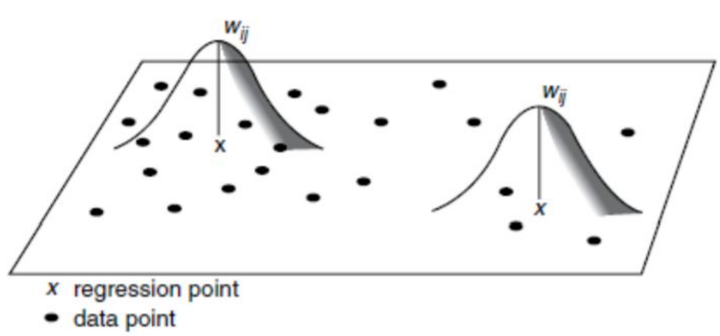


Figure 4-10: GWR with fixed kernel (Fotheringham et al., 2003)

To solve the problem, the spatial kernels in GWR can be employed by adapting the size of variations in the density of the data (Fotheringham et al., 2003). The kernel, thus, has flexible bandwidths: larger bandwidths where the data is sparse and smaller bandwidths where the data is plentiful. A commonly-used adaptive kernel function is the bi-square distance decay kernel function:

$$\begin{aligned} \mathrm{w}_{\mathrm{s,j}} &= \left[1 - \left(-\frac{\mathrm{d}_{\mathrm{s,j}}}{\mathrm{h}_s{}^2}\right)^2\right]^2 \mathit{when}\ \mathrm{d}_{\mathrm{s,j}} \leq \mathrm{h}_s \\ &= 0\ \mathit{when}\ \mathrm{d}_{\mathrm{s,j}} > \mathrm{h}_s \end{aligned} \tag{16}$$

Weight $\mathrm{w}_{\mathrm{s,j}} = 1$ when the distance equals to zeros or the point is at the center *s,* and $\mathrm{w}_{\mathrm{s,j}} = 0$ when the distance between the point and the center is equal to the bandwidth. Similarly, when the distance is greater than the bandwidth, the weight equals zero. The selection of the bandwidth considers that the number of observations with non-zero weights is the same at each location s across the study area. Therefore, the adaptive kernel function adjusts itself based on the size of the data density variation. It has larger bandwidths where the data is sparse and smaller ones where the data is denser (see Figure 4-11).

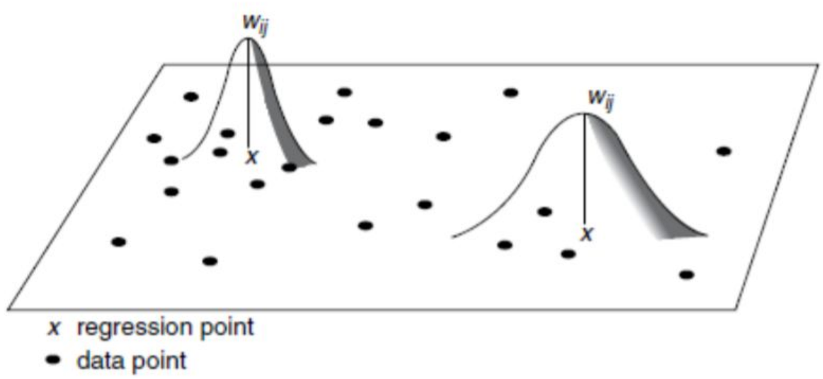


Figure 4-11: GWR with adaptive kernel (Fotheringham et al., 2003)

To evaluate model performance, a standard regression diagnostic such as r^2 (i.e. percentage of variance in the dependent [response] variable accounted for by a variance in the model), is traditionally used. The *t* value is often used to evaluate model performance. The *t* value refers to the ratio between a parameter estimate and its standard error.

Because, in GWR, the regression equation is calibrated independently for each observation, a separate parameter estimate, *t*-value, and goodness-of-fit is calculated for each observation. These values can therefore be mapped to provide a visual interpretation of the spatial distribution of, not only the nature but also strength of the relationships between predictors and response variables. For more information on the theory and practical application of GWR, the reader is referred to (Brunsdon et al., 1996, Brunsdon et al., 1998, Cho et al., 2010, Fotheringham et al., 2003, Fotheringham et al., 1998, Koutsias et al., 2005, Martínez-Fernández et al., 2013, Oliveira et al., 2014, Wang et al., 2005).

4.5.5. Selection of bandwidth

The estimated parameters in the GWR model depend on the weighting function of the selected kernel. The problem is how to select an appropriate bandwidth which requires determining the appropriate scale to analyse the data. The GWR model provides a solution to this problem by means of several criteria that can be used for bandwidth selection.

The Akaike Information Criterion (AIC) is one of the techniques that can be used to select bandwidth (Fotheringham et al., 2003). Minimising the AIC provides a trade-off between goodness-of-fit and degree of freedom. The AIC is defined for the GWR model as the following:

$$\mathrm{AIC} = 2\mathrm{n}\log_{\mathrm{e}}(\widehat{\sigma}) + \mathrm{n}\log_{\mathrm{e}}(2\pi) + \mathrm{n}\left\{\frac{\mathrm{n} + \mathrm{tr}(\mathrm{S})}{\mathrm{n} - 2 - \mathrm{tr}(\mathrm{S})}\right\} \tag{17}$$

where n is the sample size, $\widehat{\sigma}$ is the estimated standard deviation of the error term, and $\mathrm{tr}(\mathrm{S})$ refers to the trace of the estimated matrix which is a function of the bandwidth. Generally, the lower the AIC, the closer is the estimate of the model to the reality. Thus, the best model and the most appropriate scale for the analysis of the data is the one with the smallest AIC values. This criterion can also serve to indicate the goodness-of-fit of a model. In this study, the value of AIC was computed and used to compare different models.

4.5.6. The GWR's outputs

Fotheringham et al. (2003) pointed out that GWR determines parameter estimates as minimum outputs. It also determines the associated standard errors of parameter estimates at regression points. If a regression point is equal to the sample point, the GWR then generates fitted values (i.e. the dependent variable predictions), residuals and standardised residuals. The local r^2 values are generated in some implementations.

Otherwise, if the regression points are not the same as the sample points, there are three scenarios of GWR's output: First, if the independent variables for the regression points are not available, then the GWR only generates parameter estimates and standard errors. Second, if independent variables are available, the GWR generates fitted values in addition to parameter estimates and standard errors. Third, if a dependent variable is present as well, the GWR then generates the whole range of outputs (Fotheringham et al., 2003).

The GWR output can be mapped in using visualization tools such as ArcGIS to explore spatial heterogeneity or non-stationarity across the study area.

4.6. SUMMARY

In this study, the quantitative approach was used in order to understand the spatial and temporal behaviour of residential fire patterns. The quantitative approach was chosen because it was considered the most appropriate for addressing the research aim and associated research questions. The Markov chain technique was applied to examine the probability of fire occurrence by allowing for essential statistical dependence in space and time lag. The Markov chain was used to model sequential dependencies that influence the spatial dynamic of fire risk as a geographic phenomenon. Geographically Weighted Regression was applied to investigate the local effect of spatial characteristics on residential fire risk. The Geographically Weighted Regression was used as an extended variation of the global model (i.e. Ordinary Least Square) to provide a better understanding of local variations of fire risk across space which is not captured by the global model. Those two models fit into the fire dataset and census data for the Melbourne Metropolitan region throughout a ten-year period.

The next chapter will discuss the results of estimating probability of fire occurrence by using the Markov chain model. Initially, the data will be validated to ensure the reliability of the findings.

CHAPTER 5
RESIDENTIAL FIRE RISK ESTIMATION

5.1. INTRODUCTION

This chapter discusses the Markov chain method applied to estimate residential fire risk. The method is used to compute the probability of residential fire occurrence based on the past fire history of Melbourne city, Australia. A discussion is also drawn based on the key findings which are related to space and time context.

This chapter consists of five sections. Section 5.2 discusses the pre-processing of data including data validation and testing of assumptions. Section 5.3 presents the results from the Markov chain modelling. Section 5.4 provides a discussion of the key findings. Section 5.5 summarises and concludes this chapter.

5.2. DATA PRE-PROCESSING AND ANALYSIS

5.2.1. Data validation

Data validation is the data cleansing process to ensure the quality of data in terms of accuracy and usefulness. A simple technique to ensure data quality is the plotting of data. Figure 5-1 shows the plot of data series from June 2005 to May 2015. It can be seen that there is an anomaly for some data such as September 2005, January 2006, February 2006, and March 2006. The number of fires occurring during those months is likely not consistent with others. There is some missing data and even for February 2006, the value is zero (see Table 5-1 for details).

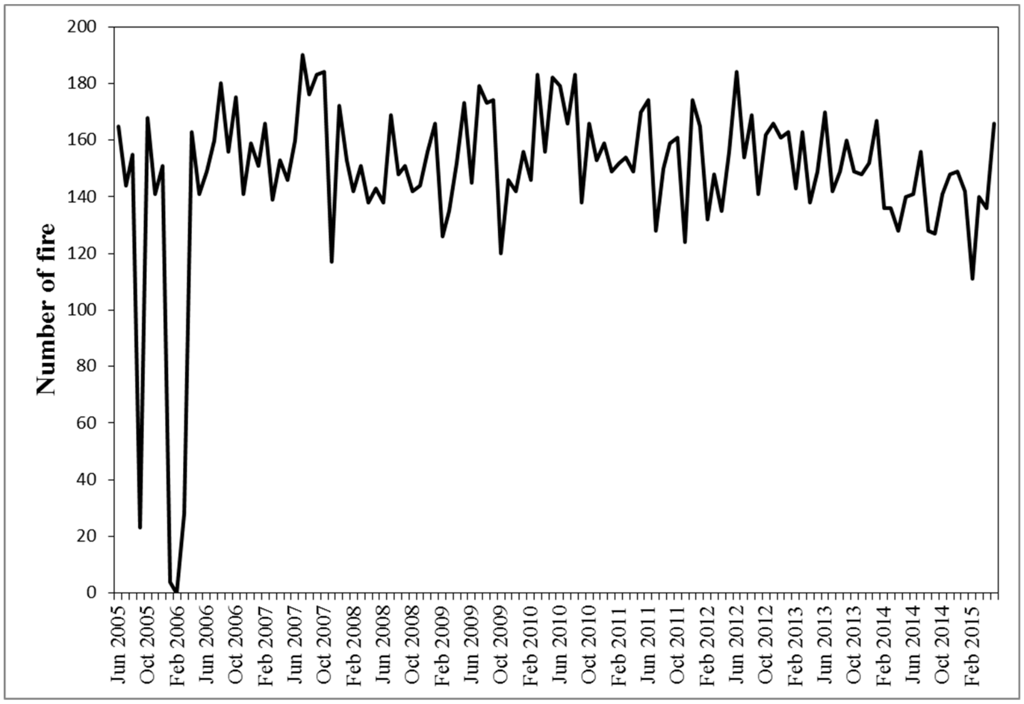


Figure 5-1: Time series plot of data from June 2005 to May 2015

Therefore, to provide a well-defined guarantee of fitness, accuracy and consistency, the data series from April 2006 to May 2015 were used. Hence, for that period, the total number of residential fires attended by the MFB in Melbourne was 16,869.

Table 5-1: Data series form June 2005 to May 2015

	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
2005						165	144	155	23	168	141	151
2006	4		28	163	141	149	160	180	156	175	141	159
2007	151	166	139	153	146	160	190	176	183	184	117	172
2008	153	142	151	138	143	138	169	148	151	142	144	156
2009	166	126	135	152	173	145	179	173	174	120	146	142
2010	156	146	183	156	182	179	166	183	138	166	153	159
2011	149	152	154	149	170	174	128	150	159	161	124	174
2012	165	132	148	135	156	184	154	169	141	162	166	161
2013	163	143	163	138	149	170	142	149	160	149	148	152
2014	167	136	136	128	140	141	156	128	127	141	148	149
2015	142	111	140	136	166							

5.2.2. Statistics descriptive

Table 5-2 presents a general summary of the residential fires in the Melbourne Metropolitan based on the residential fire dataset. The majority of fires occurred in one-family dwellings (58.5 per cent) and residential buildings with over 20 units (25.6 per cent). Apartments were less likely to be affected by fire (1.7 per cent). Forty-four per cent of all residential fires began in the kitchen. Eighty-six per cent and 4.8 per cent occurred in bedrooms and lounge areas, respectively. Foodstuff left in cooking appliances (such as microwave, oven, and stoves) unattended, overheating cooking oil, short circuit in cooking appliances and careless during cooking are the expected activities or behaviour that ignited fire occurrences. Most residential fires occurred either in winter (26.9 per cent) or summer throughout December to February (23.8 per cent). The use of heater may also a possible explanation why fires occur more frequently in Winter.

The evening is a crucial time with 54 per cent of fires occurring at night and 46 per cent during the daytime. Evening is obviously a critical time for different areas of fire origin. In the kitchen, Early evening is the time when people are usually preparing food for dinner. Cooking is one of most vulnerable behaviour which can elevate fire risk at home. For sleeping room-originated fires, the present of residents increase fire risk during these times. Short circuit of electronic and electric devices (i.e. computers, lighting) are recoded as main causes. Smokes and cigarettes and candles are also recorded igniting fire incidents in sleeping room. In Melbourne, 31.3 per cent of fires occurred during the weekend when most activities are done at home in particular cooking activities.

Table 5-2: Characteristics of residential fires in Melbourne region, March 2006 - May 2015

Variable	Number of fires	Percentage (%)
Dwellings type		
One-family dwelling	10,444	58.5
Over 20 living units	2,790	25.6
Seven to 20 living units	1,589	8.9
Three to six living units	905	5.1
Apartment, flats	310	1.7
Area of fire origin		
Kitchen	8,005	44.8
Bed room	1,529	8.6
Lounge area	855	4.8
Laundry room	551	3.1
Garage	445	2.5
Month of fire		
June – August (Winter)	4,804	26.9
September – November (Spring)	4,408	24.7
December – February (Summer)	4,245	23.8
March – May (Autumn)	4,392	24.6
Time of fire		

Variable	Number of fires	Percentage (%)
6 pm – 5 am (night)	9,640	54
6 am – 5 pm (day)	8,206	46
Weekend fire	5,470	31.3
Fire with fatalities	35	0.002

Table 5-3 shows the distribution of residential fires in the Melbourne Metropolitan area from June 2005 to May 2015. In addition, the database indicates that more fires occur within the inner suburbs. 10,760 fires occurred in inner suburbs, followed by 2,883 fires in northern suburbs, 2,282 fires in western suburbs and 1,923 in eastern suburbs. The distribution of fire incidents across the region is likely to have a pattern of city-centric concentration since most incidents have occurred within the inner city. The distribution of fire incidents may also vary across different. The reasonable explanatory of these phenomena is spatial characteristics of areas which have association with people behaviours. Next section will discuss the key urban characteristics which influence the level of fire risk at designated suburbs.

Table 5-3: Residential fires in Melbourne region, June 2005 - May 2015

Area (SA4)	Frequency of fire throughout 10 years	Number of fire per 1000 dwellings	Number of fires per km^2
Inner	6,649	19.272	58.674
Inner East	2,005	7.708	15.271
Inner South	2,106	7.636	18.019
North East	1,736	7.162	10.344
North West	1,147	8.007	9.473
Outer East	924	7.265	8.344
South East	999	7.831	10.790
West	2283	10.533	14.143

5.2.3. Time series analysis

Figure 5-2 shows month-to-month variations from April 2006 to May 2015. The residential fire occurrences show a decreasing trend, although in mid-2007 and early 2011, the number of residential fire occurrences tended to be the highest. Figure 5-2: also indicates that there is a twelve-month seasonal trend. It shows that the same phenomenon reoccurs every year. For instance, June-July and November-December are likely to have the highest number of residential fires every year, while February-March is likely to have the lowest number of fires. Human activities during these periods might be associated with the seasonal variability in the distribution of fires.

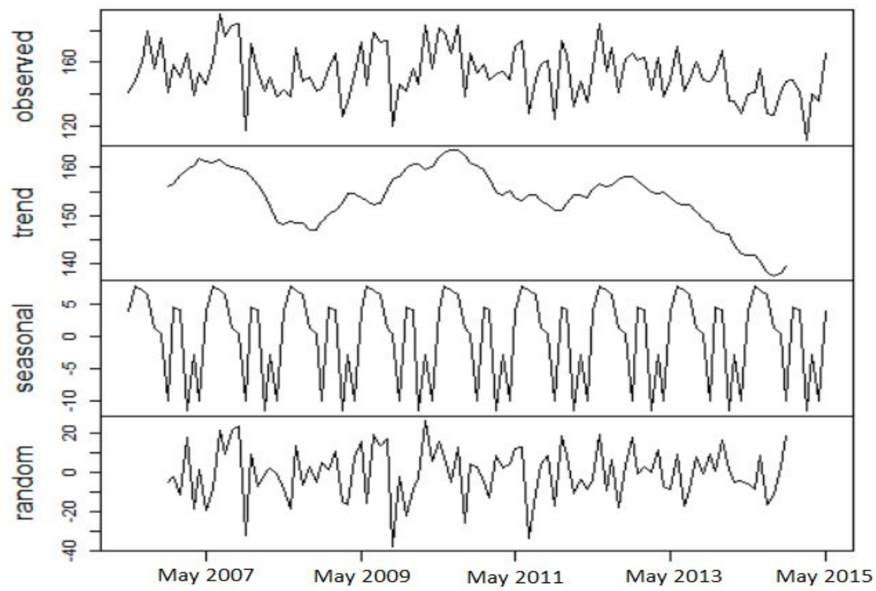


Figure 5-2: Seasonality, trend, pattern diagnostic plots for rate of residential fire occurrence for the April 2006 – May 2015 period

Figure 5-3 shows the hourly, daily and monthly patterns of residential fires in the Melbourne Metropolitan region. These figures indicate that residential fires are more frequent between 5:00 pm and 9:00 pm. The highest number of residential fires occurs between 6:00 pm and 7:00 pm (early evening) and the lowest number of fires occurs between 5:00 am and 6:00 am (early morning). The figures also indicate that fires occur mostly during weekends, starting from Friday. They also show that residential fires in Melbourne seem to occur at a relatively steady rate throughout the year.

Figure 5-4, Figure 5-5, and Figure 5-6 show the temporal patterns of residential fires according to five major areas of fire origin. Early evening is obviously a critical time for different areas of fire origin: kitchen, bedroom, lounge area, laundry room, and garage. For fires starting in the kitchen, early evening is typically the time when people cook dinner. Negligence or distraction, overheating of cooking oil, short circuiting of cooking appliances and carelessness when cooking are behaviours that are commonly known to start fires (Figure 5-4).

Different fire patterns emerge when the day of the week and the month of the year are examined. However, there is no significant difference across different areas of origin during weekends and week days except for fires originating from the kitchen. Most fires occur during the weekend when most activities are done at home, particularly cooking activities (Figure 5-5).

Throughout the year (Figure 5-6), kitchen-originated fires and sleeping area-originated fires seem to occur quite steadily. For lounge-originated fires, July is the highest period of fire occurrence. The use of a heater in the lounge area is one of the causes of fire as this is the winter season. For laundry room-originated fires and garage-originated fires, winter (especially in June) and summer (November and December) are critical periods of fire incidents as a significant number of fires occur during these periods.

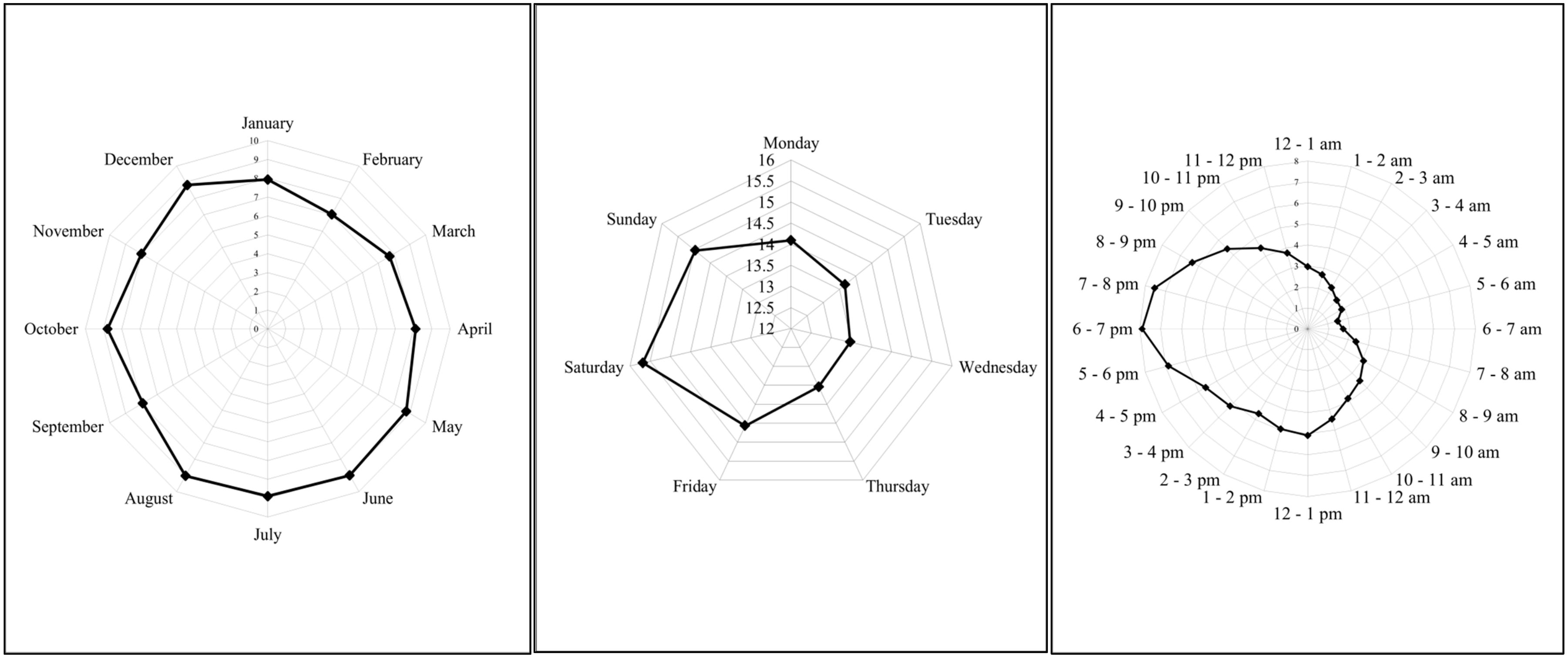


Figure 5-3: Temporal patterns of residential fires in Melbourne (all areas of fire origins)

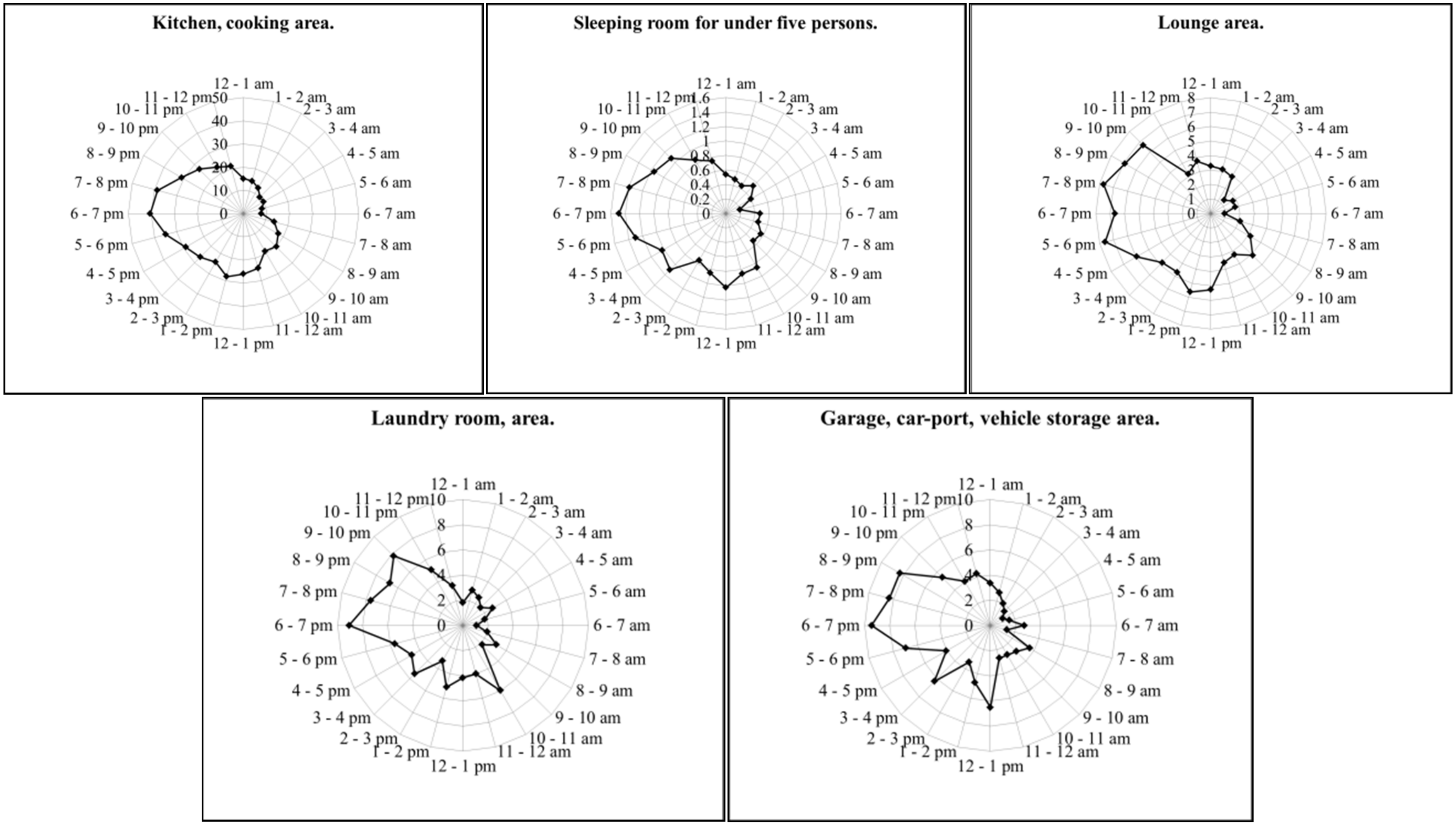


Figure 5-4: Temporal patterns of residential fires by area of fire origin (by time of the day)

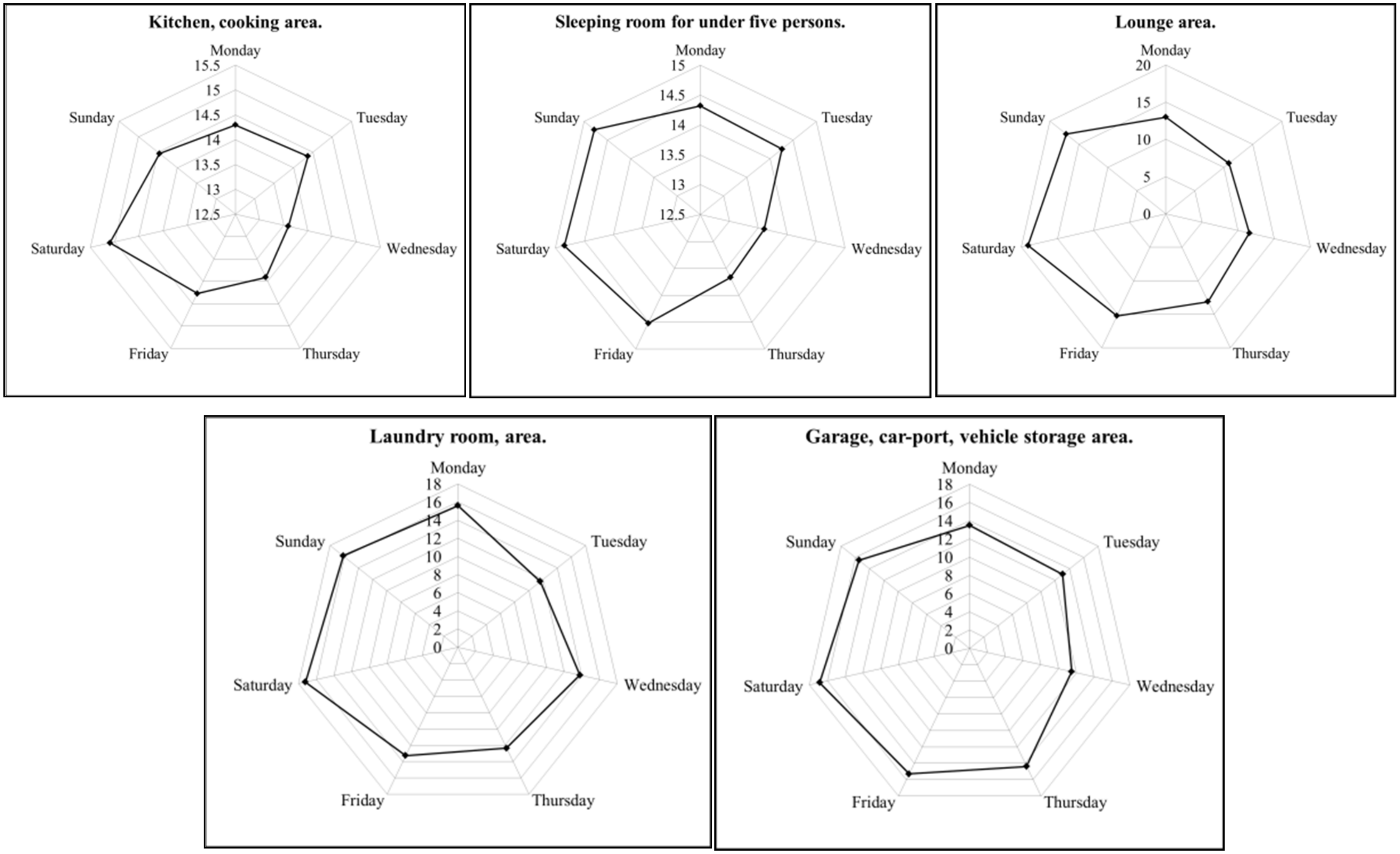


Figure 5-5: Temporal patterns of residential fires by area of fire origin (by day of the week)

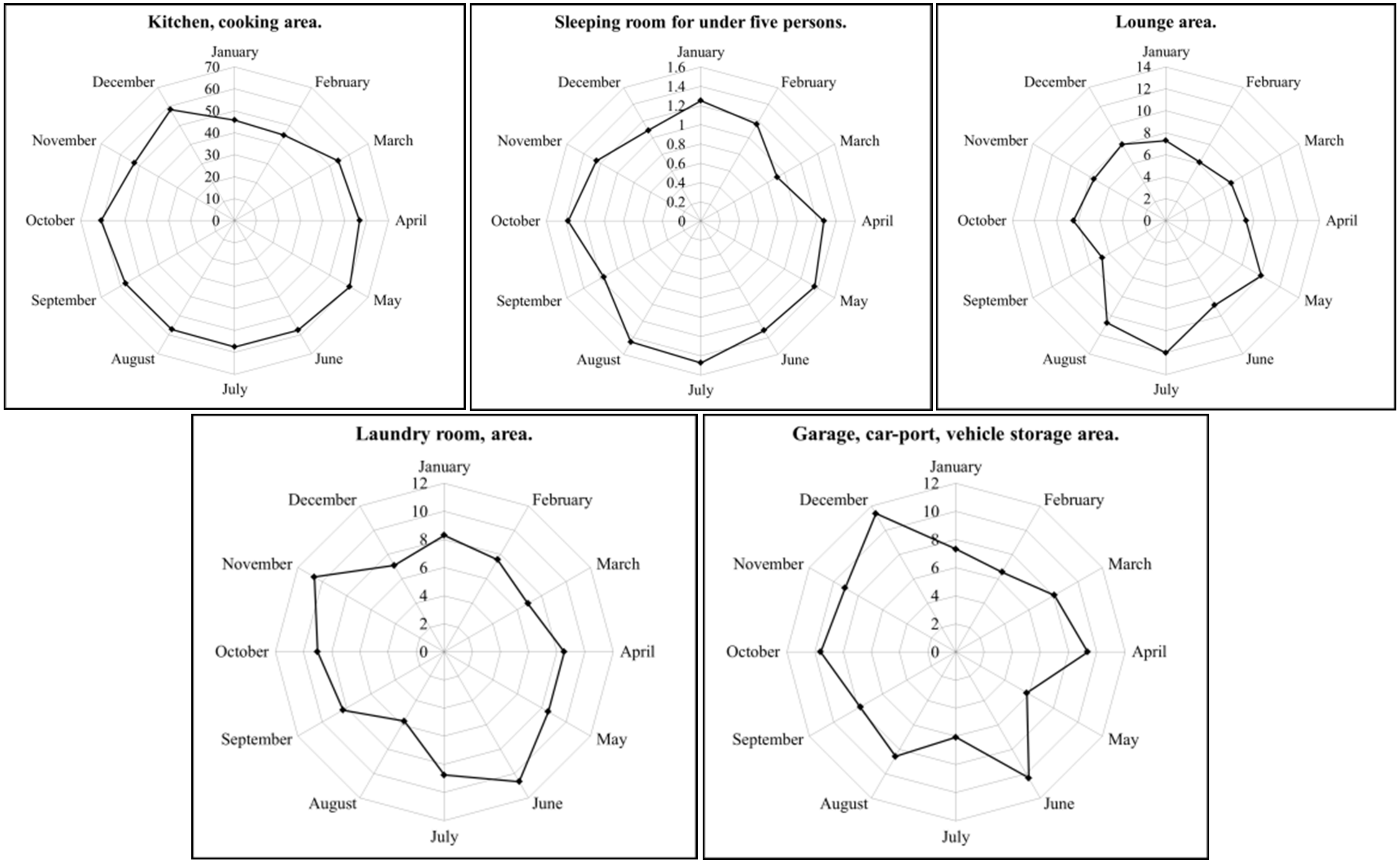


Figure 5-6: Temporal patterns of residential fires by area of fire origin (by month of the year)

5.2.4. Spatial autocorrelation test

By using the formulation described in Section 4.5, Moran's index was calculated for each year. For instance, the calculation of Moran's Index for residential fires occurred in 2007 results 0.29 with z-score of 35.09. The result indicates that given the z-score and index, there is less than 1% likelihood that this clustered pattern could be the result of a random change. In other words, high fire risk areas are clustered in close proximity to other high fire areas.

By repeating the same procedure, the spatial autocorrelation indexes for 2008 to 2014 were calculated. The 2006 and 2015 indexes were not calculated since the data for those years were incomplete. Figure 5-7 shows the trend of the spatial autocorrelation Moran's Index year by year. The indexes are likely to have slightly similar values ranging from 0.29 to 0.49. However, each year of z-score exceeds 2.58, which is at 1% significance level, meaning that the distribution of fire incidents is spatially clustered.

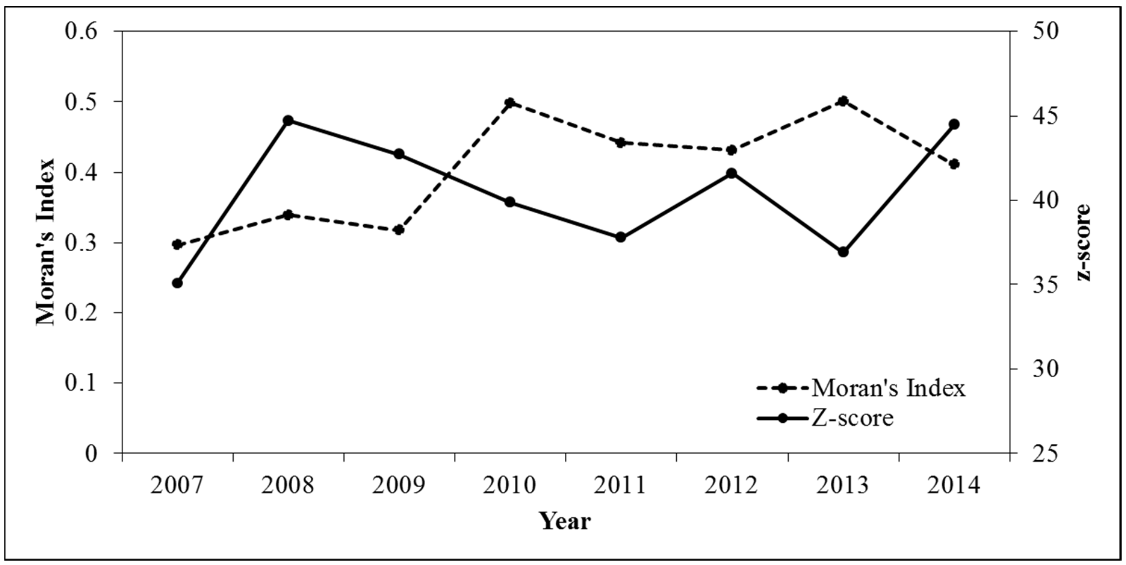


Figure 5-7: Moran's Index and z-score of residential fire distribution, year to year

5.3. MARKOV CHAIN MODEL

5.3.1. Model validation

Initially, in order to determine whether the estimations of fire risk were accurate, acceptable and valid, the model validation was conducted. The data mining approach was adopted whereby the data set, was divided into two parts: training data and test data. The training data was used to fit the Markov chain model, i.e. to estimate the transition probability. A chi-squared goodness-of-fit test is used. For each grid cell, the 70 per cent of the data is selected at the beginning as training data which consists of the fire sequence from March 2006 to July 2012, leaving the remainder (i.e. August 2012 to May 2015) as test data and then repeated the process by selecting 75 – 90 per cent of the data as training data. The objective here is to gauge the effect sampling bias has on the result obtained. After repeating the process by selecting 75 – 90 per cent of the data as training data, the results indicated the prediction accuracy as depicted in Table 5-4.

Table 5-4: Goodness-of-fit test for training data

Models		**70%**	**75%**	**80%**	**85%**	**90%**
Two-state MC	$\chi 2$	0.5044	0.2190	1.3349	0.9371	0.6154
	p-value	0.4776	0.6398	0.5130	0.3333	0.4328
Three-state MC	$\chi 2$	3.7427	3.0929	2.6056	2.0249	1.5319
	p-value	0.9967	0.9966	0.9957	0.9916	0.980

The p-value showed in the Table 5-4 indicates the degree of significance in the results. Customarily, a p-value of 0.05 or less indicates the Markov chain model provides a poor fit to the data. As is evident from the table, in the majority of cases, the Markov chain model did provide a good fit to the data. In sum, for the purpose of further analysis, the study used 80 per cent data to calculate the parameters of the Markov chain model.

5.3.2. Calculate probability of fire occurrence

By using the maximum likelihood technique, the probabilities of fire occurrence were calculated across the region given different cases. The first case is the two-state Markov chain: (i) starting with no fire incident in the past and (ii) starting with at least one fire incident in the past.

The second case is the three-state Markov chain: (i) starting with no fire incident in the past, (ii) starting with one fire incident in the past, and (iii) starting at least two fire incidents occurred in the past within neighbourhood). The following sub-section presents the results of these two cases.

5.3.2.1. Two-states Markov chain

Figure 5-8 shows the probabilities of the two-state Markov chain given no fire in the immediate past within the neighbourhood. Lower probabilities are depicted with light yellow colour and higher probabilities are shown in red colour. The natural break method is used to classify data to differentiate spatial variability in the levels of fire probability. The mapping of fire risk levels (see

Figure 5-8) shows a city-centric pattern. In the first case with no fire in the immediate past, 25 grid cells or 1.2 per cent of cells across Melbourne are at a higher fire risk (0.349 – 1), 4.0 per cent are at medium to high (0.174 – 0.348), 13.3 per cent at medium (0.090 – 0.173), 36.9 per cent at low to medium (0.043 – 0.089) and the remaining 44.6 per cent at low fire risk (0.009 – 0.042). The inner suburbs are at a higher fire risk (displayed in darker red colour) with values ranging between 0.349 – 1. In contrast, the fire risk in outer areas of Melbourne is relatively low.

In the second case given at least one fire occurred within the neighbourhood in the immediate past (see Figure 5-9), the probability of fire occurrence is more spatially dispersed across the region. Nonetheless, inner suburbs, especially south inner suburbs, still have an elevated fire risk. Compared with the first case with similar classification scheme, the map shows that 2.2 per cent of Melbourne is categorised as high fire risk, 8.2 per cent are medium to high, and 8.6 per cent are medium fire risk. The remaining cells are at low fire risk (80.9%). More areas are at lower fire risk when only one fire occurred in the immediate past within the neighbourhood.

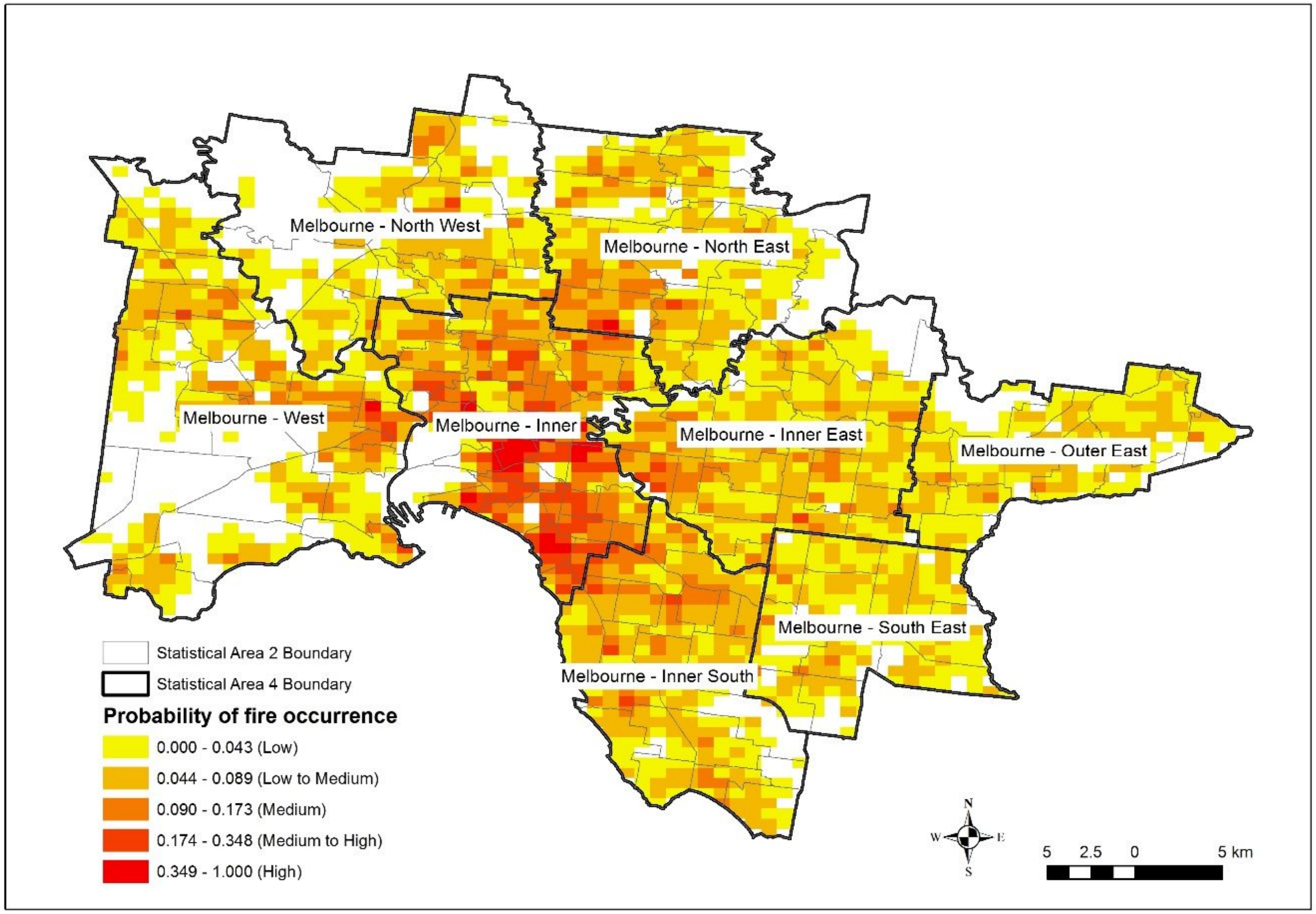


Figure 5-8: Estimated probabilities of fire occurrence given no fire incident within the designated neighbourhood using two-state Markov chain. High probabilities are indicated by dark red colour, and vice versa.

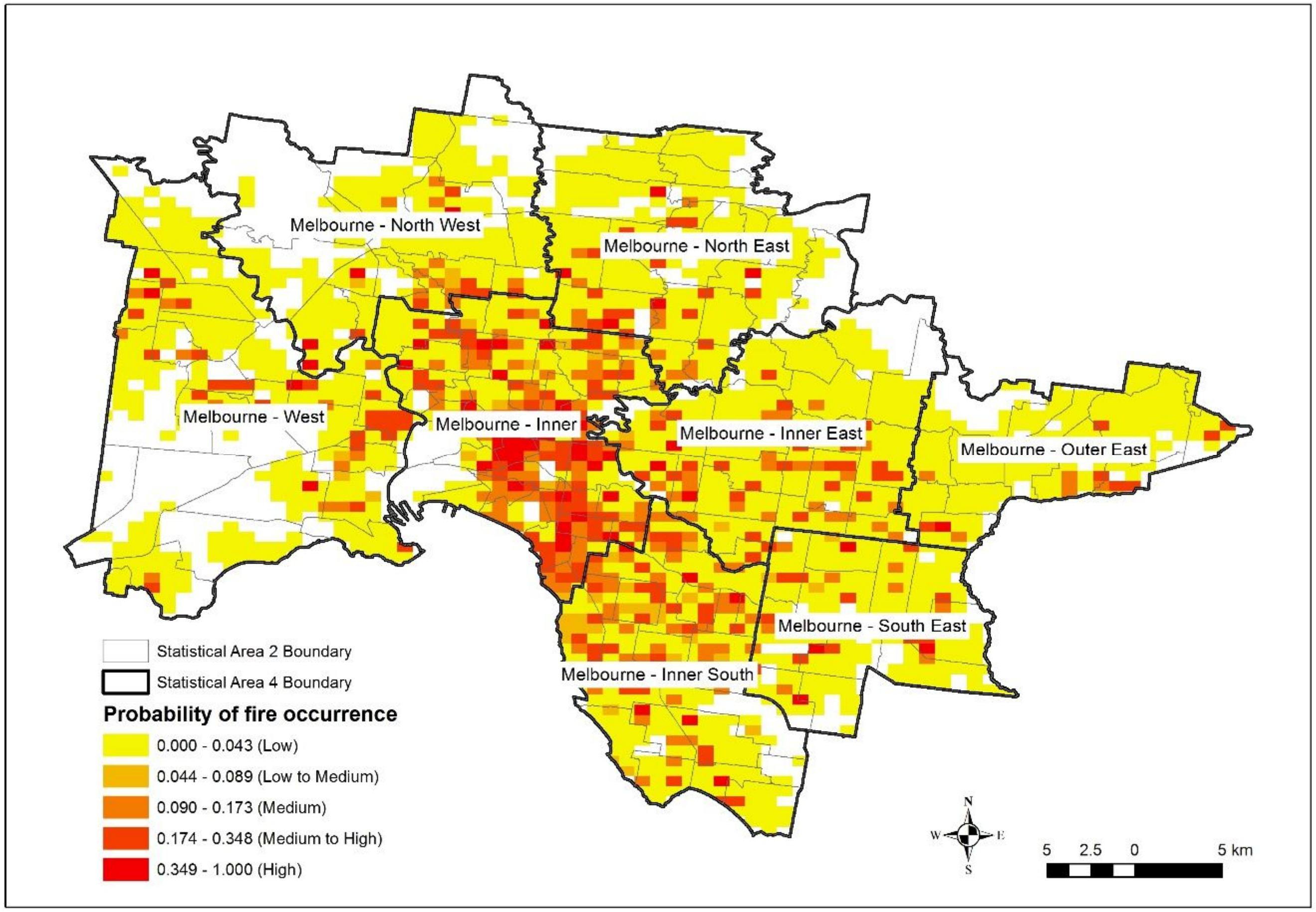


Figure 5-9: Estimated probabilities of fire occurrence given at least one fire incident within the designated neighbourhood using two-state Markov chain. High probabilities are indicated by dark red colour, and vice versa.

5.3.2.2. Three-state Markov chain

To examine the effect of the number of fire occurred in the immediate past within the neighbourhood, the three-state Markov chain was developed. By using the similar method of two-state Markov chain, the probability of a fire occurrence for each cell given three cases of starting states is calculated. In the first case, given no fire incident within the neighbourhood in the last one-month, similar results to those shown in Figure 5-8 were produced. In the second case of given one fire, Figure 5-10 shows a dispersed fire risk pattern as shown in Figure 4 was exhibited, which is similar to the second case of two-state Markov chain. Based on the same classification scheme, 2.7 per cent of cells in Melbourne are at a high fire risk level, 8.9 per cent are at medium fire risk, and more than 77.6 per cent are at a low level of fire risk. Inner suburbs are at a higher risk when compared to other suburbs given one fire within neighbourhood in the last one month.

In the third case, given at least two fires within the neighbourhood, only some areas within the inner suburbs are classified into high fire probability level. With two or more fires in the past, less than 1 per cent of cells at high fire risk while the remaining cells are at a low level of fire risk (see Figure 5-11).

The results of the models were aggregated to an administrative boundary to make the analyses more relevant for policy-making and strategic planning. Fire probabilities computed for grid cells were aggregated at the Statistical Area Level 3 and 4 (similar size to Local Government Areas). The Aggregate function resampled fire probability input raster to a coarser resolution (i.e. SA3 and 4) based on a specified aggregation operator (i.e. mean). The administrative boundaries (polygons) were intersected with the grid to compute the mean value of probabilities within each of the Statistical Areas.

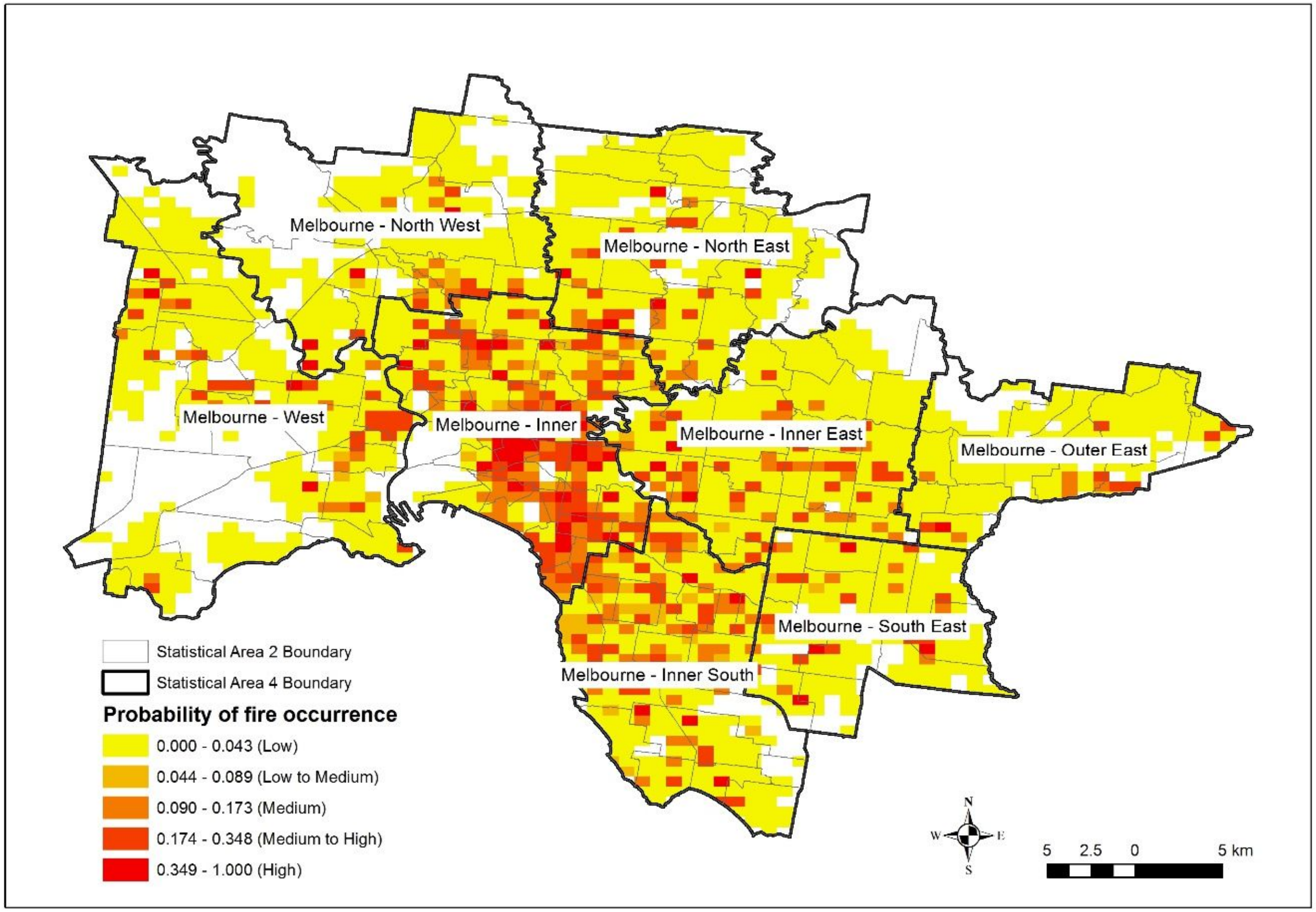


Figure 5-10: Estimated probabilities of fire occurrence given a fire incident within the designated neighbourhood using three-state Markov chain. High probabilities are indicated by dark red colour, and vice versa

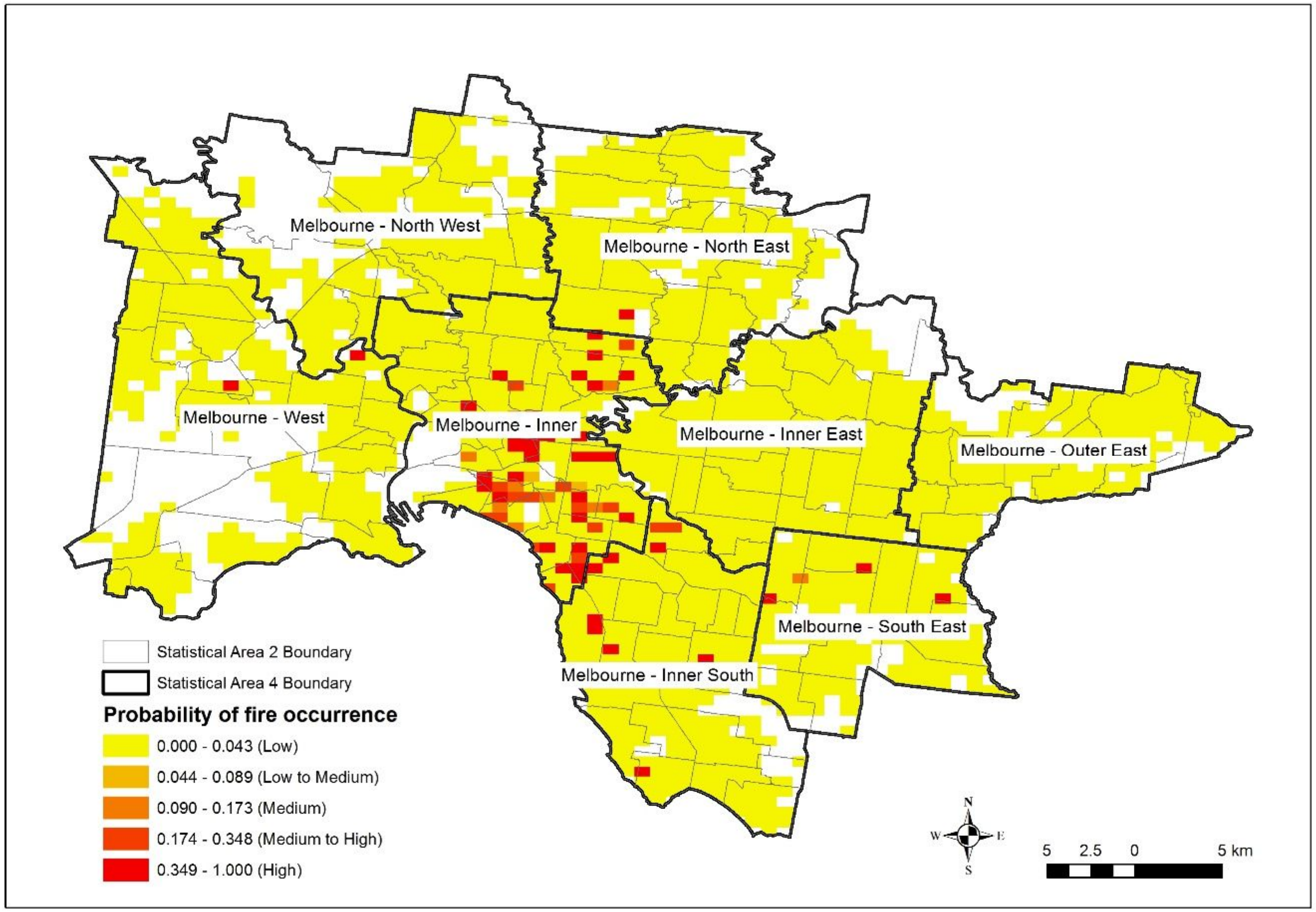


Figure 5-11: Estimated probabilities of fire occurrence given at least two fire incidents within the designated neighbourhood. High probab ilities are indicated by dark red colour; while yellow shades show lower values.

Table 5-5: Mean of probabilities across sub-region based on two-state and three-state Markov chain and comparison with traditional methods

Sub region (SA4/SA3)	Number of grid-cells	Two-state Markov chain: Mean of probability of fire given:		Two-state Markov chain: Std. Deviation		Three-state Markov chain: Mean of probability of fire given:			Three-state Markov chain: Std. Deviation			Traditional method	
		no fire	At least one fire	no fire	At least one fire	no fire	one fire	At least two fires	no fire	one fire	At least two fires	Fire frequency[1)]	Fire density[2)]
Inner	**311**	**0.125**	**0.129**	**0.133**	**0.165**	**0.125**	**0.128**	**0.079**	**0.133**	**46.197**	**28.770**	**6649**	**19.272**
Brunswick - Coburg	51	0.094	0.116	0.048	0.219	0.094	0.118	0.020	0.048	6.038	1.000	622	8.955
Darebin – South	32	0.092	0.086	0.051	0.085	0.092	0.073	0.143	0.051	2.340	4.591	402	9.777
Essendon	44	0.078	0.057	0.054	0.103	0.078	0.058	0.000	0.054	2.550	0.000	582	15.549
Melbourne City	59	0.178	0.194	0.208	0.168	0.178	0.195	0.100	0.208	14.643	7.493	2167	32.616
Port Phillip	48	0.113	0.087	0.116	0.125	0.113	0.082	0.102	0.116	6.291	7.848	1210	16.897
Stonnington - West	31	0.143	0.192	0.086	0.203	0.143	0.195	0.094	0.086	6.046	2.921	597	11.959
Yarra	46	0.149	0.159	0.140	0.166	0.149	0.159	0.095	0.140	8.290	4.917	1069	18.424
Inner East	**307**	**0.045**	**0.039**	**0.038**	**0.119**	**0.045**	**0.040**	**0.000**	**0.038**	**14.325**	**0.000**	**2005**	**7.708**
Boroondara	137	0.057	0.056	0.040	0.132	0.057	0.057	0.000	0.040	8.326	0.000	1022	8.289
Manningham - West	81	0.025	0.002	0.026	0.024	0.025	0.002	0.000	0.026	0.291	0.000	380	6.868
Whitehorse - West	89	0.055	0.063	0.040	0.141	0.055	0.064	0.000	0.040	5.708	0.000	603	7.478
Inner South	**284**	**0.052**	**0.053**	**0.039**	**0.113**	**0.052**	**0.053**	**0.022**	**0.039**	**17.117**	**7.200**	**2106**	**7.636**
Bayside	93	0.046	0.039	0.036	0.083	0.046	0.038	0.029	0.036	4.009	3.000	583	8.791
Glen Eira	98	0.075	0.086	0.043	0.134	0.075	0.086	0.032	0.043	8.499	3.167	917	7.515
Kingston	62	0.030	0.031	0.028	0.117	0.030	0.031	0.000	0.028	2.611	0.000	341	6.010
Stonnington - East	31	0.071	0.066	0.033	0.100	0.071	0.064	0.033	0.033	1.998	1.033	265	8.771
North East	**272**	**0.035**	**0.020**	**0.040**	**0.088**	**0.035**	**0.020**	**0.003**	**0.040**	**7.956**	**1.000**	**1736**	**7.162**
Banyule	105	0.027	0.017	0.029	0.088	0.027	0.017	0.000	0.029	2.861	0.000	546	6.446
Darebin - North	83	0.064	0.044	0.054	0.105	0.064	0.044	0.011	0.054	4.084	1.000	754	11.780
Nillumbik - Kinglake	1	0.005	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	1	0.358
Whittlesea - Wallan	83	0.026	0.007	0.027	0.063	0.026	0.007	0.000	0.027	1.011	0.000	435	6.416
North West	**220**	**0.023**	**0.013**	**0.032**	**0.097**	**0.023**	**0.014**	**0.000**	**0.032**	**5.547**	**0.000**	**1147**	**8.007**
Keilor	70	0.020	0.026	0.021	0.148	0.020	0.026	0.000	0.021	2.671	0.000	254	4.965
Moreland – North	67	0.051	0.025	0.031	0.066	0.051	0.026	0.000	0.031	1.869	0.000	453	9.129
Tullamarine - Broadmeadows	83	0.016	0.004	0.035	0.056	0.016	0.004	0.000	0.035	1.006	0.000	440	9.974
Outer East	**195**	**0.028**	**0.018**	**0.024**	**0.099**	**0.028**	**0.018**	**0.000**	**0.024**	**4.621**	**0.000**	**924**	**7.265**
Manningham – East	13	0.007	0.000	0.024	0.000	0.007	0.000	0.000	0.024	0.000	0.000	29	2.654

Sub region (SA4/SA3)	Number of grid-cells	Two-state Markov chain				Three-state Markov chain						Traditional method	
		Mean of probability of fire given:		Std. Deviation		Mean of probability of fire given:			Std. Deviation			Fire frequency[1)]	Fire density[2)]
		no fire	At least one fire	no fire	At least one fire	no fire	one fire	At least two fires	no fire	one fire	At least two fires		
Maroondah	109	0.032	0.019	0.022	0.082	0.032	0.019	0.000	0.022	2.593	0.000	529	8.000
Whitehorse – East	59	0.037	0.024	0.026	0.135	0.037	0.024	0.000	0.026	1.528	0.000	307	7.347
Yarra Ranges	14	0.018	0.020	0.022	0.091	0.018	0.020	0.000	0.022	0.500	0.000	59	7.157
South East	**197**	**0.032**	**0.037**	**0.026**	**0.119**	**0.032**	**0.036**	**0.012**	**0.026**	**8.559**	**3.100**	**999**	**7.831**
Dandenong	26	0.028	0.022	0.023	0.109	0.028	0.022	0.000	0.023	0.875	0.000	131	8.409
Monash	171	0.033	0.039	0.026	0.121	0.033	0.038	0.015	0.026	7.684	3.100	868	7.702
West	**343**	**0.030**	**0.018**	**0.045**	**0.108**	**0.030**	**0.019**	**0.002**	**0.045**	**11.455**	**1.500**	**2282**	**10.533**
Brimbank	177	0.030	0.018	0.035	0.106	0.030	0.019	0.004	0.035	5.221	1.000	1025	9.709
Hobsons Bay	90	0.023	0.012	0.034	0.113	0.023	0.012	0.000	0.034	2.212	0.000	514	11.282
Maribyrnong	63	0.075	0.050	0.067	0.115	0.075	0.054	0.007	0.067	4.021	0.500	681	11.442
Wyndham	13	0.006	0.000	0.024	0.000	0.006	0.000	0.000	0.024	0.000	0.000	62	10.916

1) throughout ten year-period
2) fires per 1000 dwellings

Table 5-5 shows the summary of the mean of probabilities across statistical areas based on two-states and three-state Markov chains. The results indicate similar spatial fire risk patterns to those illustrated in the grid model. The Analysis of Variance (ANOVA) was used to test whether there are significant effects of past fire occurrence within the designated neighbourhood in the last one month across the grid cells. There are two factors employ for this test: the three cases of the probability (i.e. starting with no fire, one fire, and at least two fires in the immediate past) and Statistical Areas. The F-value of 55.96 (with F-critical = 2.053 at $\alpha = 0.05$) result indicates a significant difference in the probabilities of fire occurrence among the cases. The result affirms that the probability of fire occurrence with no fire within the vicinity of neighbourhood is relatively higher than both for areas with one fire and at least two fires in the last one month Furthermore, this indicates that fire occurrences within the neighbourhood especially with a greater number of fire in the last one month are more likely to contribute in the reduction of the probability of a fire in Melbourne.

5.3.3. Month-to-month variation in the probability of fire

Fire risk relates to an action that increases the likelihood of a fire occurring. Fire risk is estimated when a change occurs from one state to another (i.e. from no fire to a fire). This transitioning of state could occur on a daily, weekly, monthly or annual basis. It depends on the phenomenon. For bushfire in Australia, it could be sessional or annual; whilst for earthquake it could be decadal or a century. In this study, fire risk is modelled on a monthly basis given the frequency of fire per unit of area. Figure 5-12 shows the k-step transition probability where one step represents one month. It depicts the change in the probability of fire occurrence in certain steps (i.e. months). In the case of at least two fires within the neighbourhood, the probability of next fire tends to decrease over the next two months and then becomes steady afterwards (solid line). Given one fire in the past, the probability of a fire also slightly decreases after two months and then stabilised to a steady state. Thus, the time threshold of reduced fire risk is about two months (dashed line) after the occurrence of at least a fire in an area. If there has been no fire within the neighbourhood in the past, the likelihood of a fire is relatively constant and uniform across the metropolis (dot line).

The results show that there is a significant difference in the variability in slopes between probability distributions across steps. Two and more fire incidents in the past tend to significantly reduce fire risk levels within the first two months in comparison to the state of at least one fire or no fire.

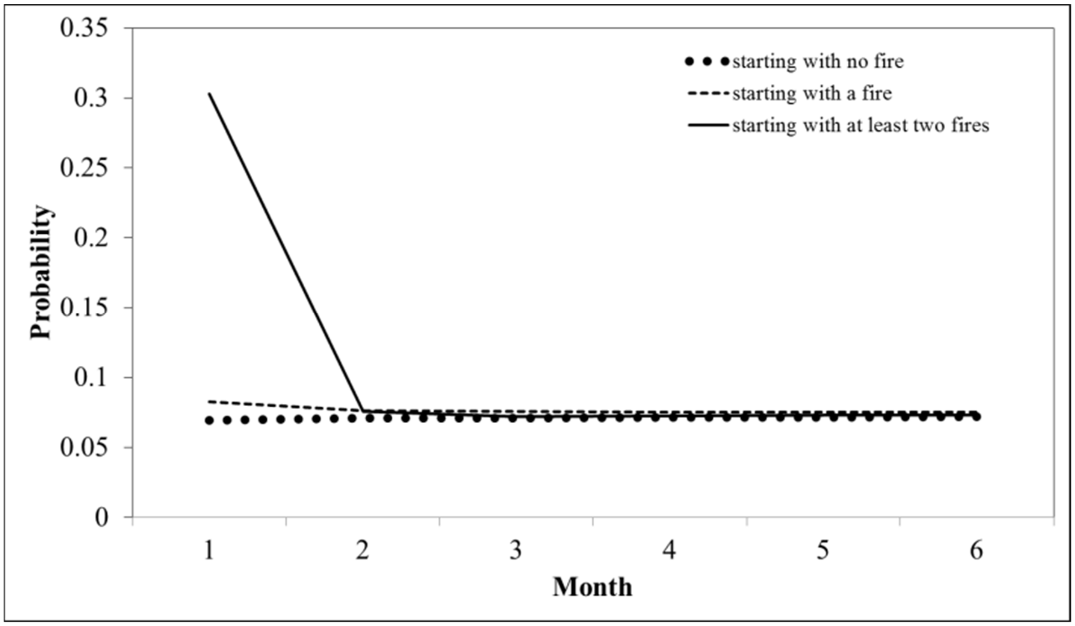


Figure 5-12: The month-wise probability of fire occurrence

5.3.4. The effect of past fire across different distance zones

The probabilities of fire occurrence based on past fire incidents were calculated for three designated zones (i.e. within 2.5 km, 2.5 km – 5 km, and beyond 5 km). Figure 5-13 shows that fire incidents that have occurred within the designated zones significantly influence the probability of fire occurrence. In the case of two or more fires occurring within designated zones the probability of fire occurrence tends to slightly reduce (dot line) until the third-order neighbours. Whilst, given one fire within the first-order of neighbours, the probability of fire occurrence is relatively low and remained constant across different zones. But, given one fire occurred beyond the second-order neighbours, the probability of fire occurrence is drastically higher than when given one fire within a cell and first-order neighbours (dashed line). Similarly, given the case of no fire within the first and second order neighbours, the probability of fire occurrence is relatively constant, but risk increases drastically when there was no fire incident up to the third-order neighbours and beyond (solid line). The second-order neighbours which are confined within 5 km from the focal cell is a threshold distance where number of fire occurred in the past has a contribution towards increasing the fire risk level when there is no fire in the past and decreasing the fire risk when there were more than two fires occurred in the past. In fact, there are 47 fire stations across Melbourne, therefore, one fire station encompasses about 15-20 km of areas so that the information of distance effect is crucial to fire agency to strategically maintain the individuals or community awareness of fire risk in particular in the areas with no fire incidents over the distance of 5 km from targeted areas. This is to ensure a low level of the probability of fire occurrence in the future.

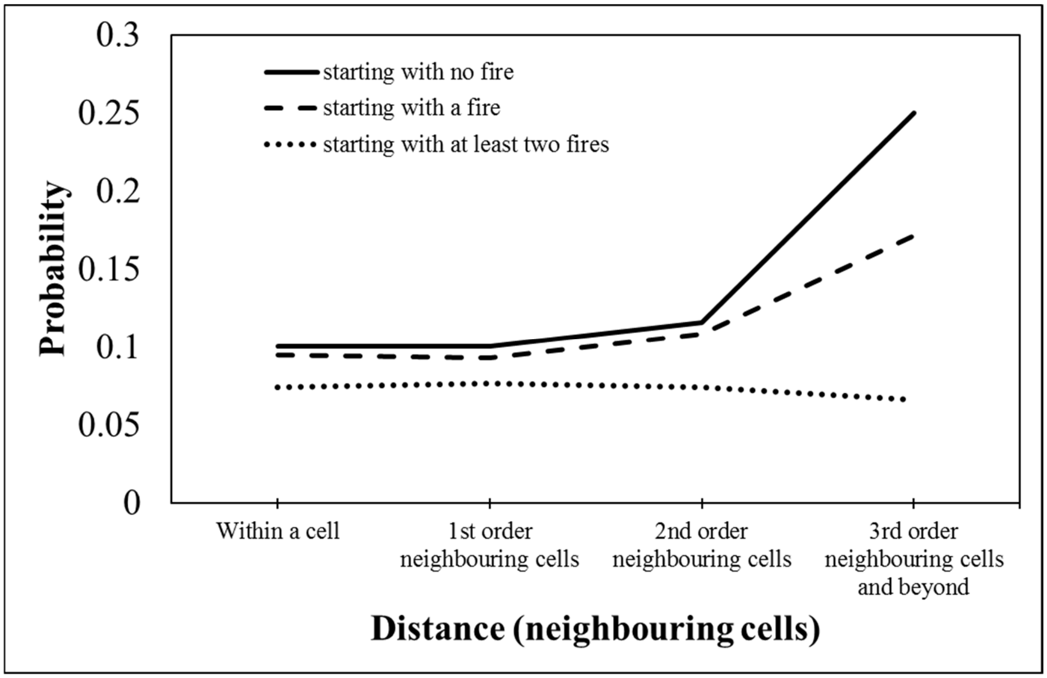


Figure 5-13: The mean of distance-based probability of fire occurrence if given starting state is (solid line) no fire incident occurred within the neighbourhood; (dash line) at least a fire incident occurred within the neighborhood, using the two-step Markov chain

5.4. KEY FINDINGS

Three key findings can be drawn from the outputs of the Markov chain analysis. First, it was anticipated that previous fire incidents would have a significant influence on residential fire incidents in the present and future. The number of fires in the past, in our case in the last month, negatively contributes to the level of residential fire risk (i.e. probability of fire occurrence). The Markov chain model showed in Figure 5-8, 5-9, 5-10 and 5-11 also indicates similar results in terms of two or more fires occurring in the past tend to gradually decrease the probability of fire occurrence. Table 5-5 also affirms that the probability of fire occurrence with no fire within the vicinity of neighbourhood is relatively higher than both for areas with one fire and at least two fires in the last one month. Furthermore, this indicates that fire occurrences within the neighbourhood especially with a greater number of fire in the last one month are more likely to contribute in the reduction of the probability of a fire in Melbourne.

Second, fire incidents that have occurred beyond a threshold distance tend to have little effect on the reduction of fire occurrence in the future. As shown in Figure 5-13, fire incidents that have occurred beyond the second-order neighbours – a threshold distance, have a contribution to increase the fire risk level rather than reduce the level, although at least one fire occurring within the zones. Conversely, in the case of given two or more fires within the designated zones, the level of fire risk gradually decreases until beyond a threshold distance. This means that areas with two or more fire incidents in the immediate past have less chance of having a fire.

Thirdly, for about a two month-period, the occurrence of at least one fire within a neighbourhood has a significant effect on the reduction of fire risk level in the next period. After this period of two months, the likelihood of a fire occurrence increases to the normal baseline or to at least the same level as that in areas with no fire. Figure 5-12 shows the trend of the probability of fire occurrence in certain months which have significant different for each case (i.e. starting with no fire incident in the past, starting with one fire incident in the past, and starting at least two fire incidents occurred in the past within neighbourhood) over the first two months.

There are two parallel theoretical perspectives that can explain the findings: the critical role of local learning and the potential memory effect on people's behaviour. As discussed in Chapter 2, a local learning effect is associated with acquiring new knowledge or information through a localised network. It is accepted that people's behavioural responses are influenced by what they have learned from their own experiences or through direct observations (deeper impact) or by the information obtained from local communication channel such as interpersonal communication (i.e. mouth-to-mouth) or local newspapers, national news, or community safety campaigns. Moreover, people who have strong geographical proximity or emotional connections to fire events might have a higher level of information retention (Clode, 2010, Kumagai et al., 2004). This shows the role of space in impeding the diffusion of information (Jones et al., 2013). However, the scale and intensity of information diffusion is expected to begin to dissipate once a certain distance from the event is reached, as awareness of that event becomes weaker beyond this distance. This is often referred to as the 'distance decay effect'. Thus, the findings support the first law of geography (Tobler, 1970, p. 236) which suggests that "everything is related to everything else, but near things are more related than distant things".

Subsequently, the findings indicating temporal dependence can be attributed to the memory effects of the residents who are more likely to be better prepared if they have experienced fire incidents in the immediate past. The ability of individuals to retain the past fire incidents which affects the reduction of fire risk in the future is, therefore, understandable. As discussed in Chapter 2, experiencing a hazard often influences risk perception. Individuals tend to be more prepared for similar incidents in the future. They change their behaviours and responses by taking any necessary action to at least reduce a similar risk. Thus, the findings are consistent with those of previous studies such as Clode (2010) which concluded that many individuals who experience such incidents are more aware of the risk rather than those who do not. The experience leads individuals to recover after any incidents and to prepare for the possibility that fire might occur in the future. Some individuals have a temporary perception while others' perceptions may be grounded in a distant past. This study found that after a two-month interval, residents still remember the incidents. After that period, the experience may not be applicable again because of changes over time to the physical environment, mobility, psychological recovery, and other factors.

In summary, residential fire risk is not only shaped by the social-spatial structure of the neighbourhood but is also related to time and its effect on people's ability to remember and recall information. This could be linked to post-fire interventions in areas where fires have occurred. This could also be attributed to the memory effect of residents who are more likely to be better prepared if they have heard or experienced a fire within the neighbourhood in the immediate past. Cognizance and awareness of elevated risk of fire might result in change behaviour, leading to better preparation and prevention of fire threats. Time is found to reduce future fire risk and should therefore be a key factor when devising and deploying fire mitigation or prevention strategies.

5.5. SUMMARY

The Markov chain model extends the traditional methods of modelling residential fire risk by innovatively incorporating the dimensions of space and time. The analysis of historical fire data provided valuable insights into the effect of space and time in shaping fire risk patterns. The first finding is related to the temporal pattern of residential fire across the Melbourne Metropolitan region. They are not uniformly distributed over time which is:

- The number of fire occurrence over a ten-year period has a decreasing trend and has a twelve-month seasonal period.
- The periods of highest fire occurrence are June-July and November-December.
- Residential fires occur more often during weekend especially on Saturdays.
- The peak time of the day when residential fire is likely to occur is 6:00-7:00 pm (early evening).

Those temporal patterns are linked to human behaviour such as cooking activities and using heaters in winter.

The second finding highlights that the mapping of the probability of fire occurrence across the Melbourne metropolis shows a city-centric spatial pattern. The inner city sub-regions are relatively more vulnerable to fire than are the outer sub-regions. These changes could be linked to a rapid rise in population in inner city suburbs due to urban consolidation and densification.

The third finding indicates that the number of past fires has a significant influence on the likelihood of residential fire occurrence. The fire risk level tends to decrease with the number of fires that have occurred in a neighbourhood. This indicates that individuals pay more attention to events that have more impact.

The fourth finding shows that there is a two-month time threshold that affects the fire risk levels within a neighbourhood. If fires occur during this two-month period, the probability of fire occurrence tends to decrease; after this period, the likelihood of fire occurrence returns at to the normal baseline, equivalent to areas with no fire. This could be linked to memory effect and the ability to remember and recall a fire incident.

The fifth finding shows that a fire that has occurred in a distant location has no significant effect on the mitigation of fire risk within neighbourhood. However, if a fire occurs within a neighbourhood, this tends to reduce the level of residential fire risk. This could be linked to the local learning effect whereby individuals tend to absorb information produced from the nearest sources. The next chapter will discuss the results of the Geographically Weighted Regression model which allows for local variability of the effects of spatial characteristics on residential fire risk.

CHAPTER 6
RESIDENTIAL FIRE RISK MODELLING

6.1. INTRODUCTION

This chapter applies the Geographical Weighted Regression (GWR) to model the relationship between the fire risk and spatial characteristics at the local level. Spatial non-stationarity in fire risk is a condition in which a simple "global" regression model cannot explain the relationships between some sets of variables. The results from the Ordinary Least Square and the Geographically Weighted Regression are also compared. This chapter examines the impact of urban characteristics on residential fire risk and to test whether individual regression coefficients are stable over geographic space.

This chapter consists of five sections. Section 6.2 presents the results of the Ordinary Least Square model. Section 6.3 discusses the result of the Geographically Weighted Regression. Section 6.4 provides a discussion of the key findings. Section 6.5 summarises and concludes this chapter.

6.2. ORDINARY LEAST SQUARE (OLS) MODEL

The OLS began by regressing the selected variables: *English proficiency*, *living at the same usual address for five years*, *living at the same usual address for one year*, *moved in last five years*, *moved in last one-year*, *own tenure*, *rent tenure*, *residential density* (number dwelling/km2), *type of dwelling* (i.e. separate house, semi detachable house, two-storey, three-storey, and four or more storeys). The global model was fitted.

Table 6-1: Summary of statistics for the Ordinary Least Squares model

	The Ordinary Least Squares Model				
	Coefficient	**SE**	**t-value**	**p-value**	**VIF**
Intercept	-3.2652	0.1437	-22.7156	0.0000*	---
English Proficiency (%)					
Limited English proficiency	0.0074	0.0035	2.0773	0.0378*	1.1595
Residence period (%)					
Living at same usual address for five years	0.0044	0.0029	1.5158	0.1297	3.4015
Living at same usual address for one year	-0.0052	0.0029	-1.7508	0.0801	9.0898
Moved in last five years	0.0180	0.0045	3.9571	0.0001*	4.0000
Moved in last one year	0.0009	0.0085	1.0653	0.2868	3.0776
Type of tenure (%)					
Owned	-0.0041	0.0022	-2.1227	0.0338*	3.0934
Rented	0.0047	0.0056	0.8394	0.4013	1.2382
Residential density (number of dwelling/km^2)	0.0004	0.0001	8.6214	0.0000*	1.8423
Type of dwelling (total)					
Separate house	-0.0023	0.0005	-4.2007	0.0000*	1.7437
Semi-detached house	-0.0037	0.0019	-1.8935	0.0584	1.3055
Two-storey	-0.0010	0.0166	-0.0600	0.9521	1.3900
Three-storey	-0.0118	0.0226	-0.5225	0.6013	1.6382
Four or more storeys	-0.0437	0.0131	-1.0158	0.3098	1.8754

*Statistically significant with 90 per cent confidence level

The OLS results presented in Table 6-1 show the association between residential fire risk and spatial characteristics as predictors. The results indicate that not all the predictors have a t-statistic greater than 2.58 for a significant level of 0.1, indicating that only some variables were significant on a global scale. This suggests that across the study area, residential fire risk is positively related to the percentage of people with limited English proficiency, residents' mobility, rented dwelling, and residential density, but a huge amount of the variance in residential fire risk remains unexplained. The full Ordinary Least Squares (OLS) model explained about 0.1171 per cent of the variation in fire occurrence with AICc = 7815.56221.

Table 6-2 shows the diagnostic statistics of the OLS model. The ANOVA returned a significant F value of 21.569 and the Wald statistic had a significant Chi-square value of 390.8. This means that, generally, the model proved to be statistically significant. The Jarque-Bera statistic returned a significant Chi-square value = 708,904, indicating that the model's prediction was non-biased (i.e. the residuals are normally distributed). However, the Chi-squared value (7.60) of the Koenker statistic was not statistically significant. Importantly, this indicated that the relationship between some or perhaps all of the independent variables and the criterion variable was not consistent across the study area. The explanation for this is that some independent variables may be relevant for predicting the outcome of fire in some area, but in other areas they may exhibit weak predictive capability. This requires further analysis to increase the reliability of the model and to test whether individual regression coefficients are stable over geographic space.

Table 6-2: OLS diagnostic statistics

Parameters	Full Model	p-value
Joint-F	21.5691	0.0000*
Wald	390.8002	0.0000*
Koenker	7.6002	0.8686
Jarque – Bera	708904.7836	0.0000*
r^2	0.1170	
Adj. r^2	0.1116	
AICc	7815.5622	

*Statistically significant with 90 per cent confidence level

6.3. GEOGRAPHICALLY WEIGHTED REGRESSION MODEL

6.3.1. Model selection and validation

The GWR models with different scenarios of bandwidth, a distance used for local estimation of neighbours, significantly reduced the AIC values. Table 6-3 shows the characteristics derived for each model. The Geographically Weighted Regression produced a significantly better result for all tested combinations of variables. A comparison of the AICc values for both models shows that the value decreased from 7815.5622 (for OLS reduced model) to 7713.5359 (for the GWR model). The GWR model was an improvement over the global one. The difference between r^2 for the global and that of the GWR was about 16.85 per cent, indicating the GWR model made significantly better prediction of fire risk. The GWR model has the potential to expose local patterns in the spatial distribution of a parameter, which would be overlooked by the OLS model.

A list of bandwidth against AIC suggested an optimal value for a bandwidth of 7,493 metres. This was calculated automatically by the statistical criteria of the GWR software. The grid cell size is set to a 2.5x2.5 km, so that it can still capture regional variations.

Table 6-3: Summary of fitting characteristics for the regression models analysed in the study

Model	*AICc*	*Global r^2*	*Global Adj. r^2*
OLS full	7815.5622	0.1170	0.1116
OLS reduced	7811.1155	0.1121	0.1108
GWR with bandwidth 7493 m*	**7713.5359**	**0.2855**	**0.2594**

*The best-fitted model

In order to show the local properties of the GWR model in more detail, the values of r^2 are mapped on the red-yellow-blue colour scale in Figure 6-1. Red, orange and yellow colours indicate areas where the GWR model provides a better fit than global models. From the figure, it can be seen that in the eastern part and some of the western part of the study area, the values of r^2 are relatively low rather than other regions. It reveals that the local regression model is performing poorly in this part of the study area. The inner suburbs and the northern part have relative higher values of r^2 ranging from 0.11 to 0.30, and it indicates that the local model is performing better in this part of the study area. Consequently, there is a significant improvement in the global model from 0.11 to 0.30 depending on the location. GWR can predict about 20 per cent better that the global model.

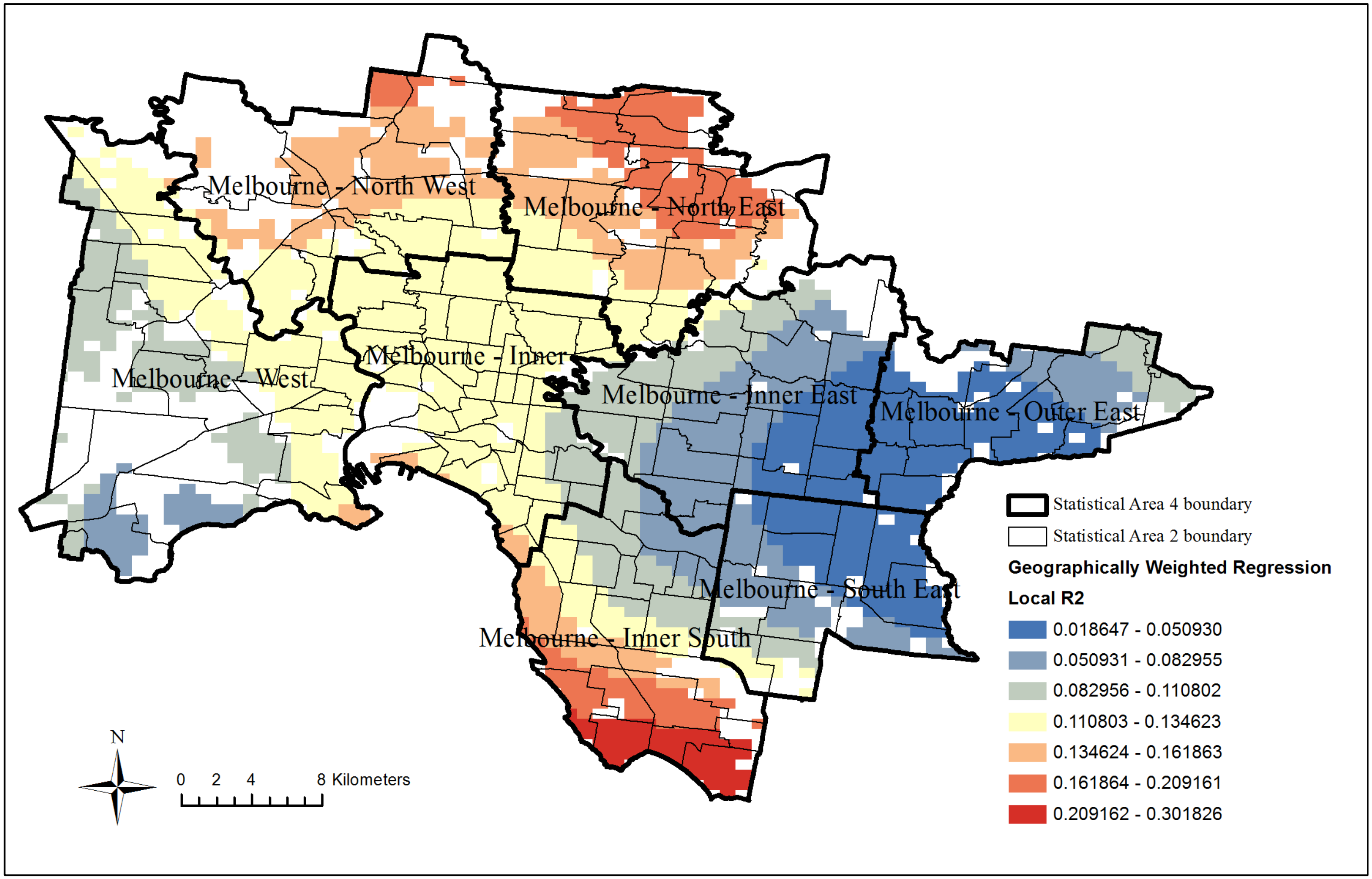


Figure 6-1: Local r^2 for the GWR model. The colour scale indicates where the GWR provides a better fit compared to the global models.

Figure 6-2 and Figure 6-3 show that the standardized values of the residuals having a mean of zero and standard deviation of one. The mapping of the values of the standard residuals indicated that fire risk is spatially dependent. High values surround high values, and low values surround low values. The values of standardized residuals are used to determine whether the model predicts well, under-predicts or over-predicts values. Points of interest are the statistically significant clusters of very high values are greater than 2.5 times the standard deviation and very low values are less than 2.5 times the standard deviation. These values indicate where certain explanatory variables are missing from the model. As shown in Figure 6-2, except for a part of the western suburbs where values were under-predicted and inner suburbs where values were over-predicted, the standard residuals obtained from the OLS model are within the 2.5 standard deviations of the mean. Comparing this to the GWR model, the standard residuals obtained from the model are within 2.5 standard deviations, meaning that the explanatory variables used in the model can be captured by the predicted model (Figure 6-3).

Additionally, the spatial autocorrelation test for the residuals of the models was conducted to assess the randomness in the residual pattern. The Moran index of each model was calculated. The value of the Moran index for the OLS model was 0.037 and the p-value for the hypothesis that this value was not significantly different from zero is 0 ($Z = 8.302$). Normally, this indicates that the hypothesis is accepted. The pattern of residuals is clustered. Whilst, the Moran index for the GWR model residuals was 0.002 ($p = 0.563$), indicating a significant confidence of any autocorrelation in the residuals; there is a randomness of the residuals. This indicates that GWR improves the reliability of the prediction.

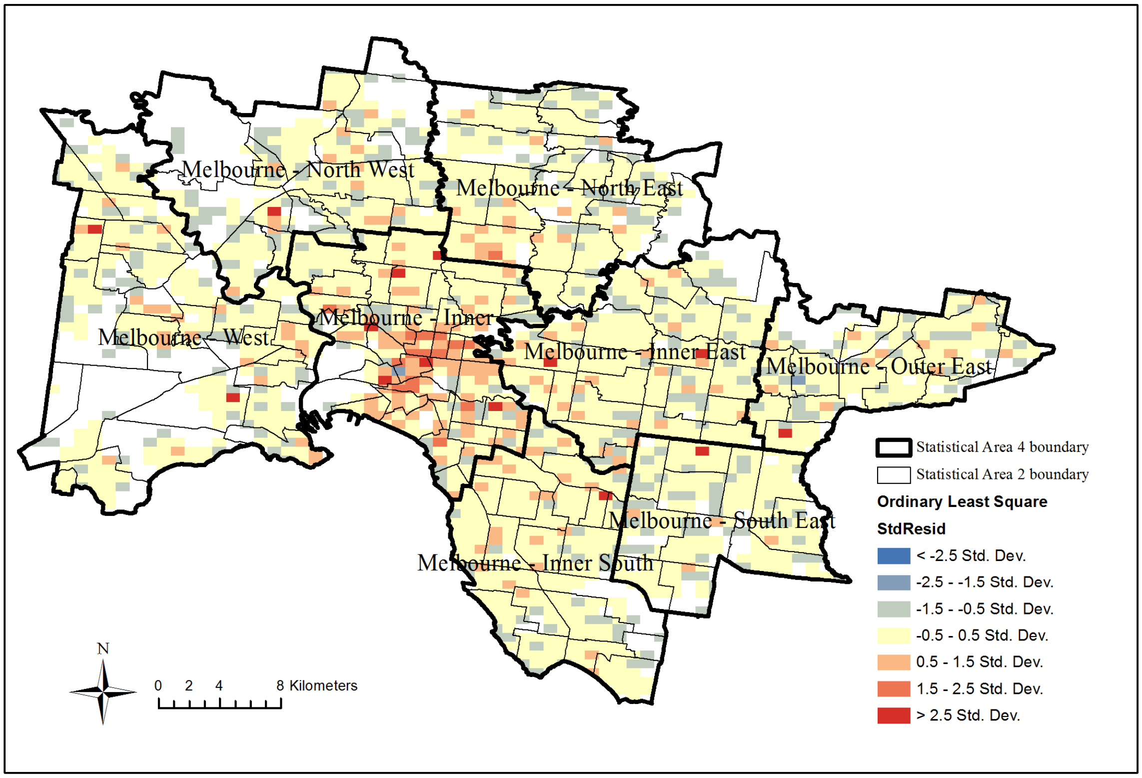


Figure 6-2: Standard residuals of the Ordinary Least Square model

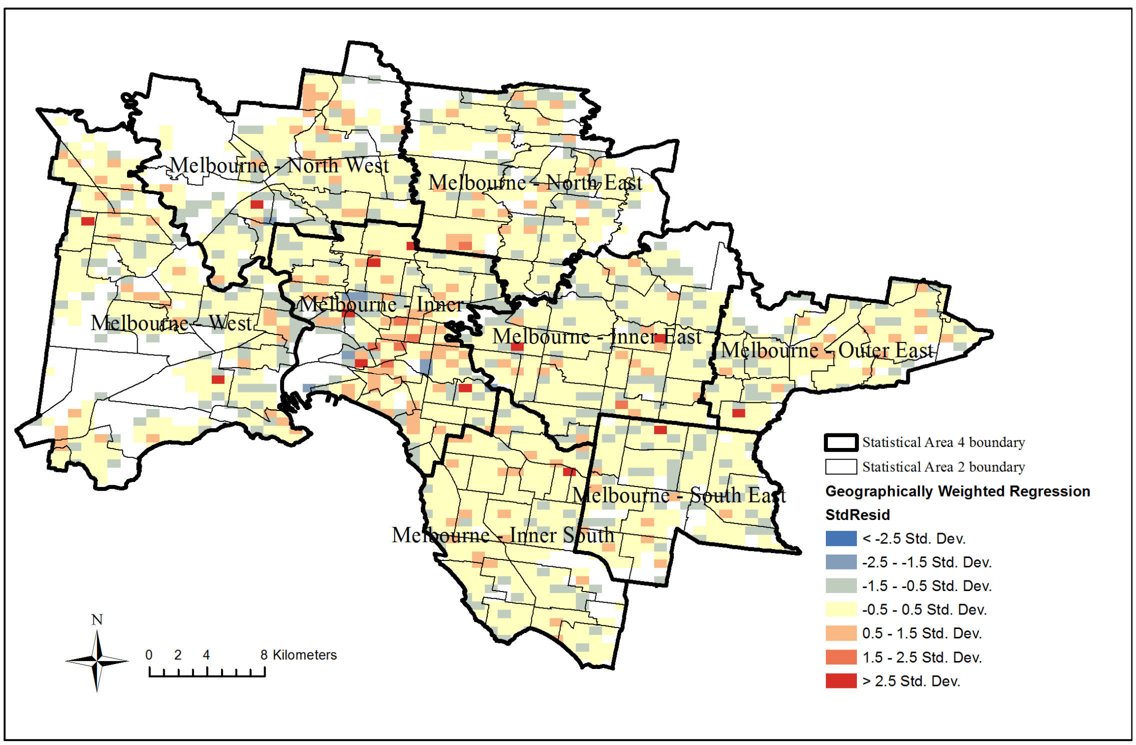


Figure 6-3: Standard residuals of the Geographically Weighted Regression model

6.3.2. Parameter estimation

The local parameter estimates for the GWR model varied in magnitude and direction. Their spatial patterns illustrated the geography of the relationships between fire risk and geographic factors. Table 6-4 summarizes the descriptive statistics obtained for the parameter estimates of selected covariates of the GWR model. Thus, the intercept parameter $\hat{\beta}_0$ has a median of -3.5493 with a range of -4.2779 to -2.0738; the percentage of people with limited English proficiency parameter $\hat{\beta}_1$ has a median of 0.0064 with a range of -0.0075 to 0.0342; the residential mobility parameter $\hat{\beta}_2$ has a median of 0.0128 with a range of -0.0021 to 0.0322; the ownership parameter $\hat{\beta}_3$ has a median of -0.0053 with a range of -0.0155 to 0.0053; the total separate house parameter $\hat{\beta}_4$ has a median of -0.002 with a range of -0.0033 to 0.0008; the residential density parameter $\hat{\beta}_5$ has a median of 0.0004 with a range of 0.0001 to 0.0009.

Table 6-4: Descriptive statistics for the parameter estimates

Variables	Parameter	Min	1st quartile	Median	3rd quartile	Max
Intercept	$\hat{\beta}_0$	-4.2779	-3.71686	-3.5493	-3.0595	-2.0738
Limited English proficiency	$\hat{\beta}_1$	-0.0075	-0.0002	0.0064	0.0131	0.0342
Residential mobility	$\hat{\beta}_2$	-0.0021	0.0062	0.0128	0.0180	0.0322
Home Ownership	$\hat{\beta}_3$	-0.0155	-0.0080	-0.0053	-0.00004	0.0053
Separate house	$\hat{\beta}_4$	-0.0033	-0.0023	-0.002	-0.0011	0.0008
Residential density	$\hat{\beta}_5$	0.0001	0.0003	0.0004	0.0006	0.0009

6.3.3. Local variability

GWR allows the display and visualization of the parameter estimates of each explanatory variable on a raster surface. This enables the complex relationship that varies over space to be understood more easily. The resultant surface raster for the predictors shows that there is spatial variation in the relationship between residential fire risk and its related spatial variables across the region. Positive and negative relationships are indicated by the results of GWR. The positive correlation means that as the specific explanatory variables increase, so does the fire risk. Otherwise, a negative relationship is implied as a specific explanatory variable increases, fire risk correspondingly decreases. Local coefficient estimates for each explanatory variable are presented in Figure 6-4 to Figure 6-8. The colour ramp is graduated from light to dark. Areas with light shading are those where that particular variable has a strong influence on fire occurrence, while the dark shading indicates areas where that specific variable has a weak or low influence on fire occurrence.

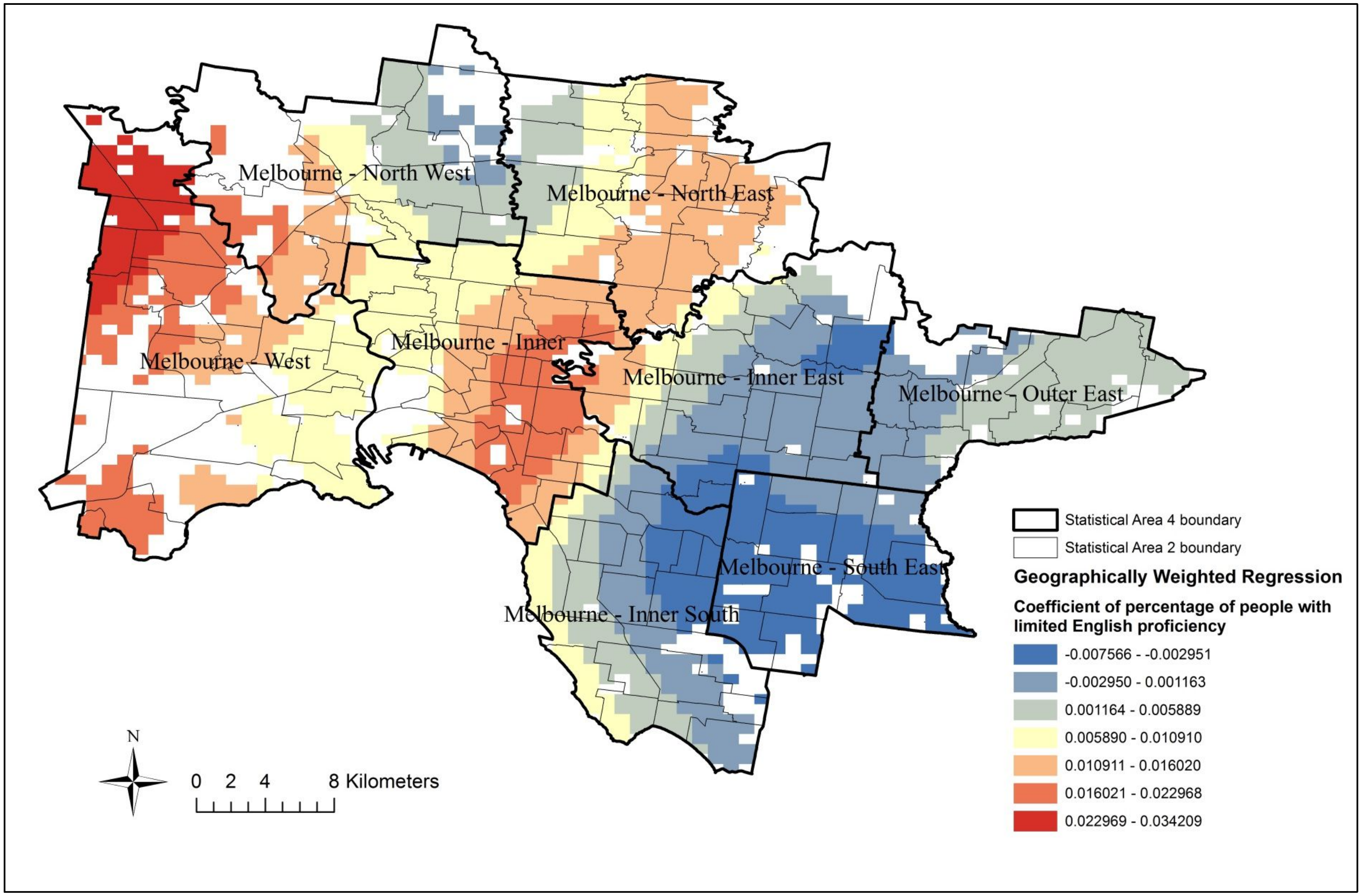


Figure 6-4: Geographically Weighted Regression local coefficients of percentage of people with limited English proficiency

Figure 6-4 shows that the influence of the percentage of people with limited English proficiency is in the western and south-eastern suburbs. Due to this resultant parameter estimate which has both negative and positive signs, the variables of the percentage of people with limited English proficiency has a strong positive influence on the risk of fire occurrence in parts of the western suburbs and the eastern part of inner suburbs. It can be inferred that the more people with limited English proficiency, the higher is the level of residential fire occurrence.

This finding is expected because this factor can affect the ability of the community to communicate, interact and exchange fire risk information within the neighbourhood. If people have a lower level of English proficiency, information about past fire incidents within the neighbourhood is relatively difficult to transmit throughout the neighbourhood. In addition, language could be a barrier to social and spatial interaction and thus affect the level of spatial interaction (Meischke et al., 2010). However, a unique phenomenon is occurred in south-eastern areas which the influence of this variable has strong negative values, meaning that although there are fewer people with limited English proficiency, the fire risk is still likely to be at a high level. It can be inferred that, not like other areas, in south-eastern, the English proficiency is not a barrier in risk information communication. The explanation of phenomenon will be explained through the influence of another variables. Overall, the map shows that more culturally diversified areas are likely to have a stronger effect on fire risk in the west of Melbourne. The scale of this effect reduces with the south-easterly direction, except for the higher density inner city suburbs.

Figure 6-5 shows the effect of the percentage of people who have moved in the last five years on fire risk levels. The map depicts areas of high positive values where the strong influence can be seen in and around the city centre with a highly mobile population base (ABS 2011). The higher the ratio of people who have frequently moved in the last five years to the total residents, the higher is the level of residential fire risk. More stationary residents tend to have higher levels of social cohesion and spatial interactions, which helps with communicating risks and threats to the community. Residents living for a longer period in the same area are more likely to develop a sense of belonging which in turn affects the local interactions. It is also related to the possibility of having a fire experience. Residents who move frequently are likely to have less change of experiencing a fire incident, whereas having past fire incidents influences individuals to be more aware for the possibility of similar incident in the future (Keane et al., 2002, Clode, 2010). Overall, the map shows that greater mobility of residents within areas is likely to have strong effect of levelling residential fire risk in the inner suburbs. The magnitude of this effect reduces with an outward direction, in particular the outer-easterly direction.

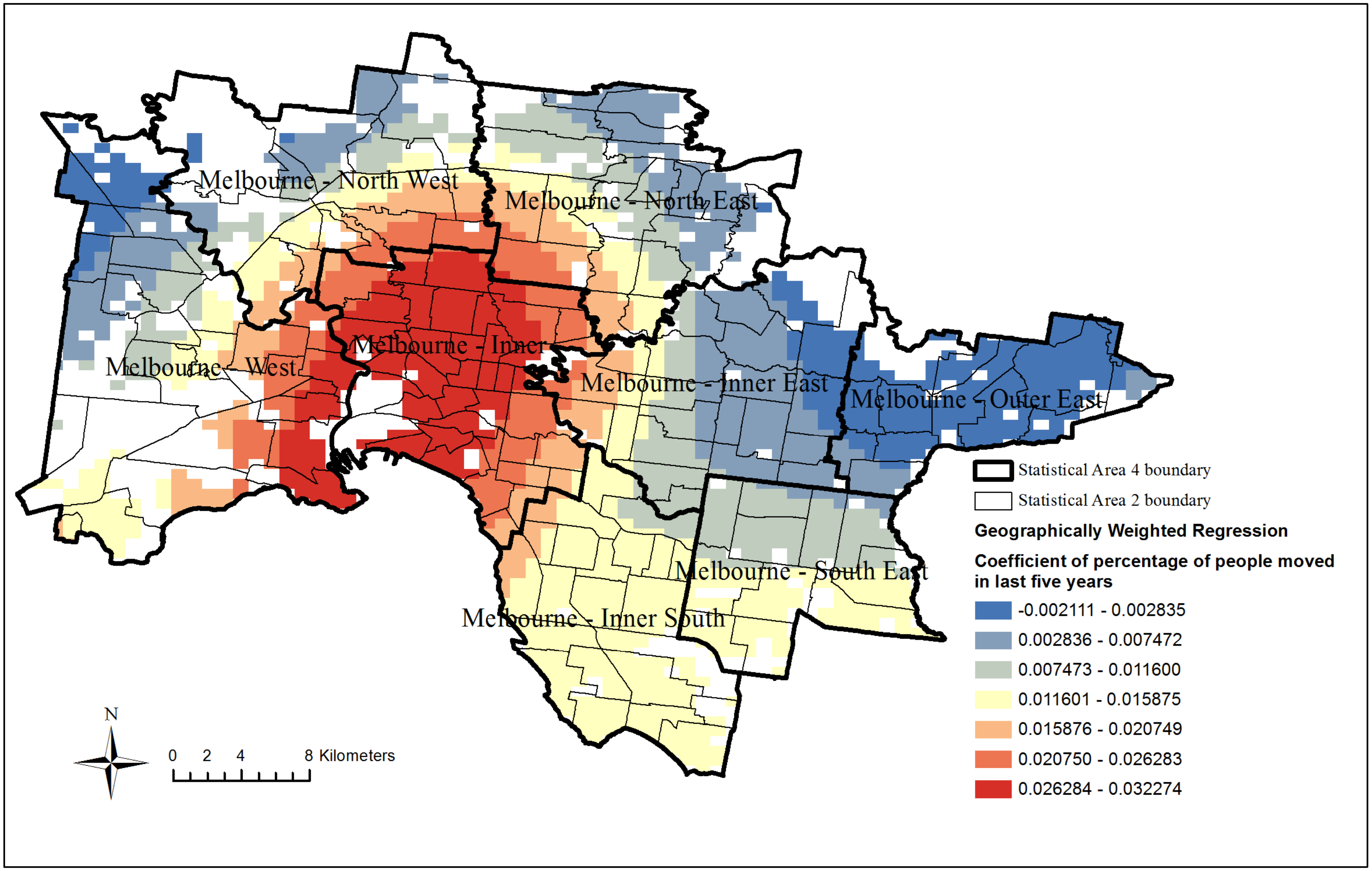


Figure 6-5: Geographically Weighted Regression local coefficients of percentage of people who moved in last 5 years

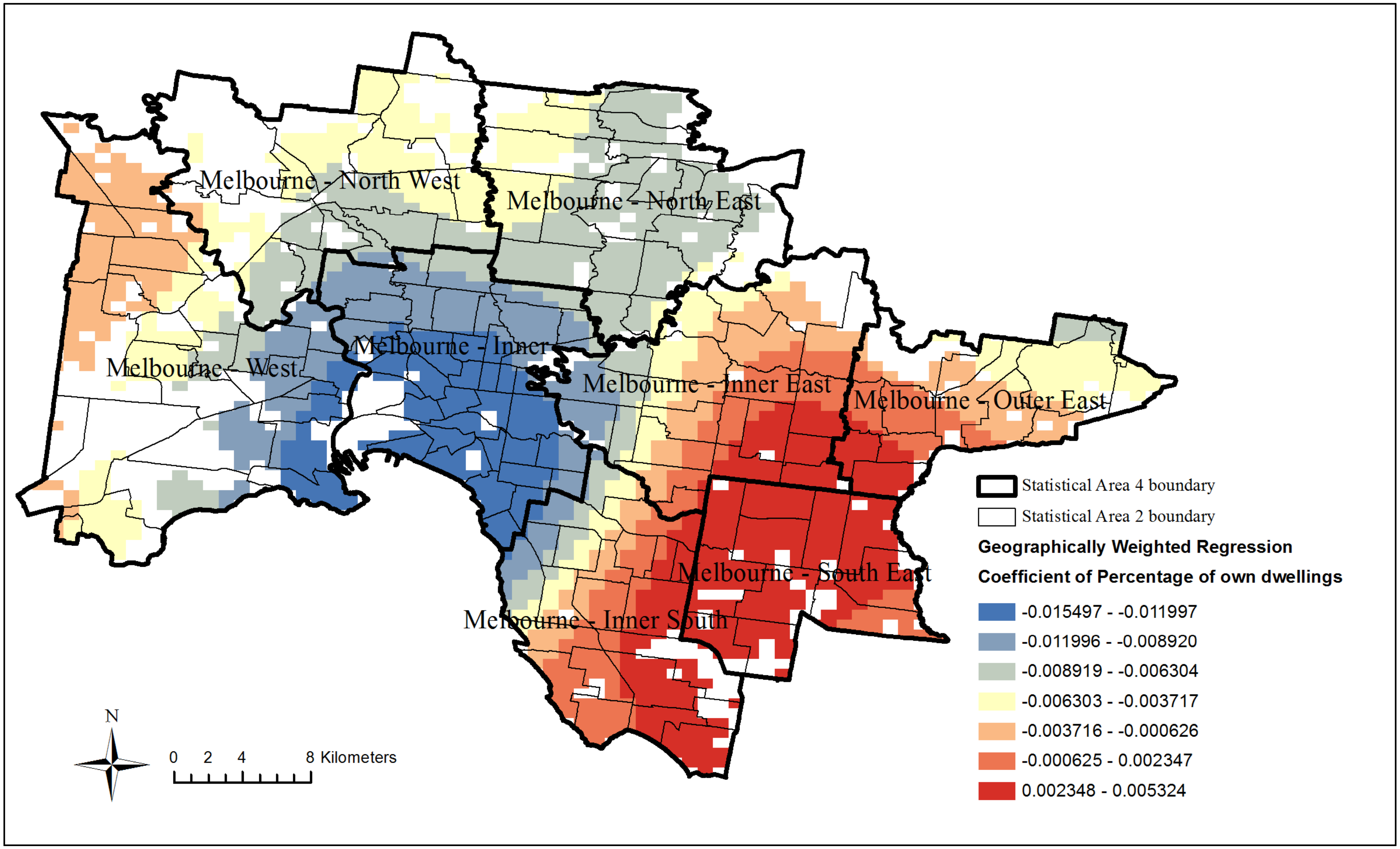


Figure 6-6: Geographically Weighted Regression local coefficients of percentage of own tenure

Figure 6-6 shows the spatial variability of the impact of home ownership, with higher values in parts of the western and south-eastern suburbs. In contrast, home ownership seems to have a negative effect in the southern part of inner, inner east, north west and north east areas. The high proportion of home owner seems to mitigate the fire risk level in these areas. This is reasonable from the theoretical perspective since home owners have more spatial interaction with others and they stay longer in a particular neighbourhood. They might have experienced fire incidents in the past or have received information about fire risk more often than did the tenants (DiPasquale and Glaeser, 1999). Overall, the map shows that a higher percentage of home ownership within areas is likely to have a strong effect of mitigating the level of fire risk. The direction of the strong effect of mitigating fire risk level variable is moving from outer suburbs towards inner suburbs.

Figure 6-7 shows the spatial variability of variable of dwelling density. The residential density has stronger positive values in outer suburbs, especially in parts of the western suburbs. This means that outer suburbs with higher dwelling density are likely to increase the level of residential fire risk. Conversely, in the inner suburbs, although residential density has positive values, it seems to have a weaker influence on the residential fire risk level. The reasonable explanation about the relationship between dwelling density and residential fire risk is that of people living in areas with high dwelling density tend to have lower interaction with others in the community as well as they tend not to know each other in a larger community (Kasarda and Janowitz, 1974). It might be an obstacle in sharing or exchanging information about fire risk (Scherer and Cho, 2003). Consequently, the transformation of fire risk perception in order to mitigate the fire risk level is difficult to achieve except through other ways such as experiencing direct fire incidents. Overall, the map shows that higher dwelling density areas are likely to have a strong effect of levelling residential fire risk in the north-western region. The scale of effect reduces with the inward direction to the inner suburbs.

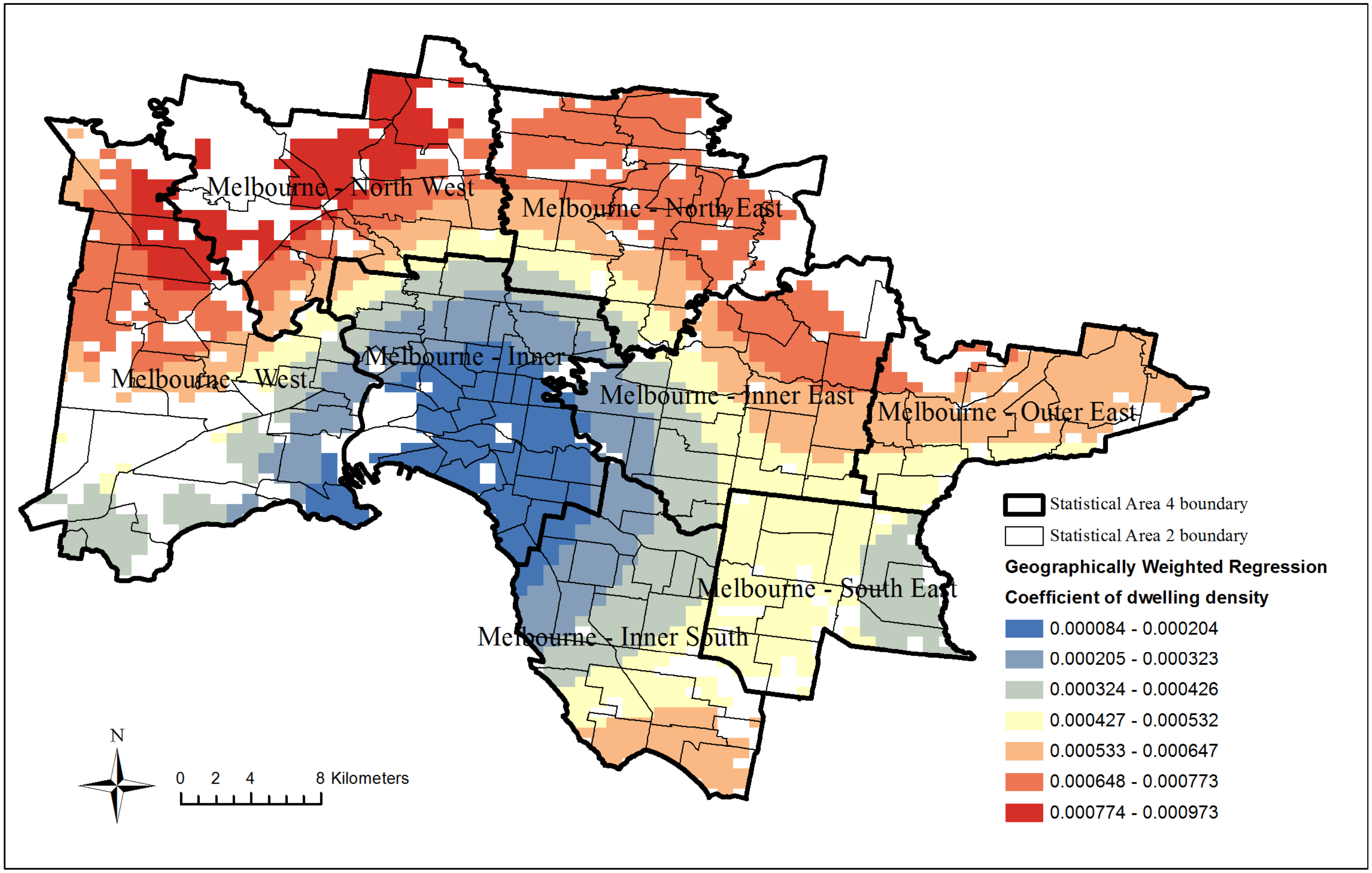


Figure 6-7: Geographically Weighted Regression local coefficients of dwelling density

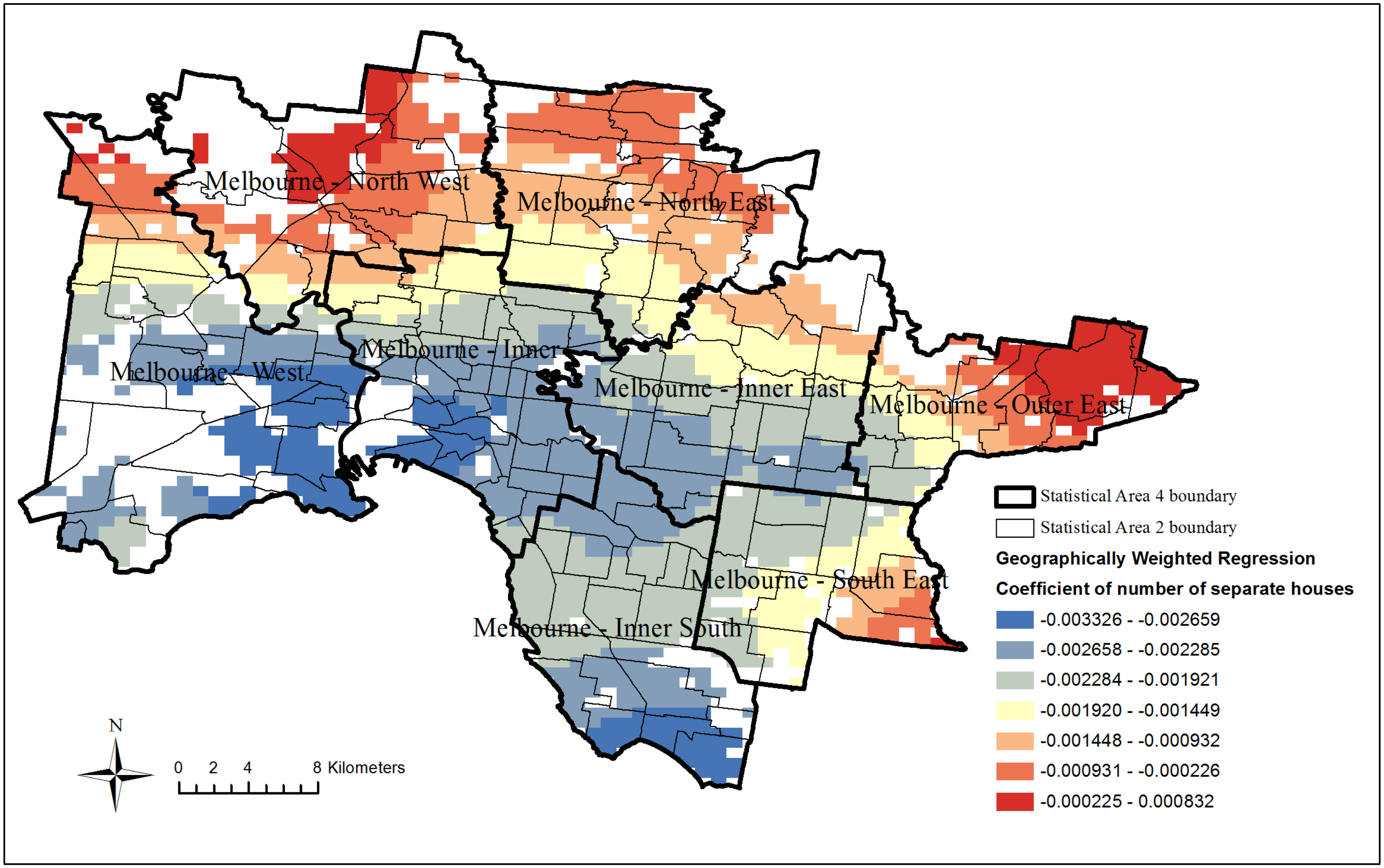


Figure 6-8: Geographically Weighted Regression local coefficients of number of separate houses

Figure 6-8 shows the spatial variability of the variable of dwelling type especially in term of separate houses. The influence of separate houses on residential fire risk shows strong values in parts of the northern suburbs. The number of separate dwellings located in this area seems to be a major factor in increasing fire risk. In the inner suburbs, a strong negative influence on residential fire risk is shown; this indicates that the higher number of separate houses in this particular area is likely to diminish the risk level of residential fire.

From the theoretical perspective, it can be explained that dissemination among resident living in separate house is easier than among those living in an apartment. These residents are likely to know each other and tend to have a strong relationship (Helleringer and Kohler, 2005). Therefore, when there is information about fire risk or the sharing of experience, it will be adopted more quickly and may successfully influence the risk perception (Scherer and Cho, 2003). Further it may mitigate the residential fire risk.

Overall, the map shows that a greater number of town houses or separate houses within areas is likely to increase the fire risk in north-western region and outer-eastern region. The magnitude of the effect turns with the inward direction.

6.4. SUMMARY

This chapter presents the results of the application of the Geographically Weighted Regression to determine the relationship between fire risk and the situated context. There are the key findings can be drawn from the outputs of the GWR. The first finding relates to the contribution of the local variability of spatial characteristics which has improved the model since the global model showed inconsistency regarding some of the independent variables across the region. Some independent variables have better predictive outcome, whilst other have weaker predicting capability. The GWR model reveals local patterns in the spatial distribution of an independent variable which is ignored by the global model.

The second finding suggests that residential fire risk is spatially dependent. It depends on the local spatial characteristics whereby each variable has a different magnitude to increase or lessen the fire risk level across different parts of the Melbourne Metropolitan region. For example, in the western suburbs of the region, there was a positive effect for the relationship between residential fire risk and the number of people with a limited English proficiency, yet the opposite applies for those people who had moved in the last five years which has a negative relationship with fire risk.

On the other hand, the stronger positive impact was due to the large proportion of people with limited English proficiency and people who moved frequently in the last five years. Those variables increased the level of residential fire risk. This interesting finding is evident in the CBD and inner suburbs. Conversely, the stronger negative relationships between English proficiency and fire risk and also between residential mobility and fire risk were indicated throughout the south-eastern suburbs. It suggests that a lower proportion of people with limited English proficiency and moving less frequently within the south-eastern suburbs are likely to indicate a higher level of fire risk. This type of profile suggests that limited English proficiency and residential mobility in the south-eastern region are not likely to be a barrier to spatial interaction which would prevent the sharing or exchanging of information about fire risk.

The third finding shows that each variable has a different direction of strong effect. The strong effect direction of the limited English proficiency variable is moving from west to south, while the direction of strong effect of the residential mobility variable is moving from the centre (i.e. inner suburbs) to the outer suburbs. Conversely, the direction of strong effect of the home ownership variable is going the opposite way, from the outer to the inner suburbs. A similar direction is shown for the number of separate houses, from the outer to the inner suburbs. The direction of strong effect of dwelling density is moving from the north-west to the centre of the study region.

The next chapter concludes the study with an overview of the key findings, the contributions made by this research, and the implication for planning.

CHAPTER 7
CONCLUSION AND FUTURE RESEARCH

7.1. INTRODUCTION

This chapter concludes this study by summarising the key findings and limitations of this research. It discusses this study in the light of the developed stochastic model that estimated the likelihood of residential fire occurrence and identified key urban characteristics underpinning fire patterns over time and across space. This study developed two novel techniques for modelling fire risk in order to better understand and extend the knowledge of residential fire risk behaviour in the context of space, time, and situated context. The first technique, the Markov chain model, estimated the probability of residential fire by incorporating spatial and temporal dependence. The second technique, Geographically Weighted Regression, investigated the key determinants that influence fire risk at local area level. The summary of these findings is presented in two parts: spatial and temporal patterns associated with residential fire, and residential fire risk in a situated context. The implications of these findings for planning, the contribution to the current body of knowledge and the limitation of the study are also discussed.

The chapter consists of six sections. Section 7.2 draws a conclusion of key research findings. Section 7.3 describes the planning implications of this study. Section 7.4 demonstrates how the research questions underpinning this thesis have been answered. Section 7.5 discusses contribution of this study in the theoretical and methodology framework. Section 7.6 describes the key limitations of the study and opportunities for future research.

7.2. KEY RESEARCH FINDINGS

7.2.1. Key findings on residential fire risk in space and time

- The number of fire occurrence over ten-year period has a decreasing trend with twelve-month seasonal effects.
- June-July and November-December are critical periods for fire occurrence.
- Most fire incidents occurred on weekends and in the early evening from 6:00 pm – 7:00 pm.

- Mapping the probability of fire occurrence across the Melbourne metropolis shows a city-centric spatial pattern where inner city sub-regions are relatively more susceptible to fire than are the outer sub-regions.
- The probability of residential fire occurrence (i.e. residential fire risk) can be estimated as a stochastic process whereby the change in the probability of fire occurrence in a certain area in the future, inter alia, depends on the state of fire occurrence in the immediate past. This means that whether or not there was a fire within neighbourhood in the immediate past will influence the likelihood of fire occurrence in the future.
- There is a time threshold of about two months that affects the reduction of the fire risk levels within a neighbourhood. . After this period of low fire risk, the probability of a fire increases to the normal baseline, equivalent to that of areas with no fire.
- A fire that has occurred in a distant location (i.e. beyond 5 km) has no significant effect on fire risk within a neighbourhood.

The findings suggest that residential fire patterns in the Melbourne region are related to human behaviour activities over time and space. For, instance, human activities in winter and during other cold weather spells may ignite fires in residential properties. Foodstuff left unattended in cooking appliances (such as microwave, oven, and stoves), overheating cooking oil, short circuiting in cooking appliances, and carelessness during cooking are found to be common behaviours that lead to fire. On the other hand, in terms of spatial analysis, residential fire incidents in Melbourne Metropolitan region are related to geographical characteristics. The occurrence of fires across space is not uniform and non-random. The spatial variation in the built environments may reflect the social and economic characteristics of particular areas that in turn affect fire risk levels.

Findings highlight a spatial dependence indicating the presence of link to local learning effect, which tends to reduce the probability of fire occurrence within the neighbourhood. As noted, the fire risk increases with distance from the location where the fire has occurred. It can be inferred that those residents living closer to the fire occurrence are likely to be more aware of risk factors and are perhaps better prepared to mitigate the potential risk from fire hazards (e.g. clearance of hoarding in backyard or replacement of faulty fire alarms).

On the other hand, the ability to remember and recall a fire incident is time-dependent. Residents can retain information about a fire incident in their neighbourhood and take actions to mitigate fire risk for a short period of time; however, after a period of about two months, the past fire incident has no profound effect on fire risk levels. The risk levels are affected and formulated by the way fire incidents are confronted, evaluated, cognitively processed, remembered, assimilated and connected with what we know already. Information retention can help us to understand the perception of fire risk as the result of a learning effect. Therefore, the framing of residential fire risk as a function of fire events in time and space is crucial for building a theoretically-driven fire risk model.

Overall, the findings highlight that residential fire risk is shaped by temporal and spatial dependence of fire risk. Space and time dimensions could be considered as surrogates of the local learning and the ability to remember and recall the information about risk should be key factors determining residential fire risk. Finally, these findings demonstrate that residential fire risk can be predicted as a stochastic process whereby fires that have occurred within a neighbourhood in the intermediate past contribute to the possibility of occurrence of fire in the future.

7.2.2. Key findings on residential fire risk in situated context

- The inclusion of local statistics in modelling residential fire risk contributed significantly to improve the model. Geographically Weighted Regression provides a better prediction outcome than the Ordinary Least Square model because it takes local dependency into account.
- Different areas have varying contextual situations, which influence the level of residential fire risk. The effect of socio-spatial characteristics such as language, residential mobility, home ownership, type of dwellings, and dwelling density, in relation to residential fires risk tends to vary across urban areas. Higher level of residential mobility and residents' inadequate knowledge of English have a strong effect on the fire risk level in inner suburbs; dwelling ownership, dwelling density, and the number of separate houses play a role in increasing the fire risk level in areas beyond the inner suburbs.
- Each variable has a different direction of strong effect on fire risk levels. Most variables such as home ownership, dwelling density and number of separate houses have a direction from outer suburbs towards inners suburb. In contrast, the residential mobility has an opposite direction of strong effect from the inner suburbs to the outer suburbs.

The findings have demonstrated that those covariates have served as social-spatial barriers to conveying and sharing of risk information at a local scale. Some unique local characteristics might appear to prevent on the residential fire risk in certain areas, while in other areas, they have the opposite effect. Overall, the variability in fire risk is not only space-driven and time-dependent but is also context specific. The situated context that differentiates neighbourhoods influences the levels of fire risk. These findings answer the third research question by demonstrating that the urban characteristics on that influence residential fire risk vary across urban areas.

7.3. PLANNING IMPLICATIONS

The analysis of historical fire incident data has generated new evidence to inform some of the policy questions, which were not previously been answered in the extant literature in this field. Three key planning implications derived from this study are discussed below.

Area-specific fire risk mitigation strategy

In terms of the effectiveness of resource management, the findings related to the space dimension indicate the need for a geo-targeted strategy whereby resources should be allocated to help reduce fire risk at an acceptable level. The finding demystifies the conventional wisdom currently prevailing in emergency management and practices that often emphasises the allocation of resources to areas with a high number of fire incidents. This analysis indicates that areas with a greater number of fire incidents are at a lower risk of fire in comparison to areas that have had no fire in the past. This might be linked to individuals' and communities' better awareness and preparedness that in turn might lead to fire prevention. This decreased risk might also be associated with the effect of post-fire intervention or awareness campaigns in areas of high fire incidents. It is surmised that people, in the absence of any threat, tend to become more complacent and reactive. Behavioural change is therefore needed in the community to ensure that the risk of fire is communicated and perceived in a timely manner and across all groups in the local community.

Time management of fire risk campaign

The importance of the timing of an intervention in mitigating fire risk is critical for establishing an effective risk management plan. This research indicates that there is less likelihood of a fire at a particular location because of the impact of a fire that occurred in the immediate past, although the reduction stabilises after a two-month period. This suggests that people's ability to retain and recall information about past fire(s) in their neighbourhood is more likely to be restricted to about two months. During this initial period, residents might proactively respond to potential fire hazards by implementing fire mitigation measures that in turn reduce fire risk level. They might respond to potential threats from fire by checking the working condition of smoke alarms, fire extinguishers or blankets or even by developing a fire exit plan. This might in turn result in the short-term mitigation of fire risk. Such responses might help reduce the probability of fire occurrence in the near future.

Knowing this time threshold is vital for emergency planners when scheduling more geo-targeted interventions to improve community awareness of fire risk, first in areas where there was no fire, and later immediately after a period of two months when fire risk levels increase in areas where there was a fire. Often, fire agencies tend to react to a fire incident by implementing post-fire incident awareness campaigns; however, this research indicates that during this initial period of two months, there is a reduction in fire risk levels. However, this reduction in fire risk may be linked to risk prevention/mitigation programs that fire agencies often implement in the post-incident phase. Nonetheless, interventions are needed in areas which were not subjected to any fire incidents in the immediate past. Further research is required to support the testing and validation of these hypotheses as the propositions are heavily dependent on the data-driven approach. Nonetheless, it is concluded that timely intervention and scheduling are critical to the success of fire safety programs.

As discussed earlier, the findings of this study also indicate that people should be placed at the centre of decision-making, so that residents' ability to retain information and to memorise past fire incidents can be taken into consideration when: examining residential structure fire risk patterns especially at local community level; establishing basic strategies; and improving fire communication opportunities in clusters by targeting the best location with appropriate contextual situations such as language, residential mobility, and other factors.

Identify spatial barriers to fire risk communication in community

Knowing the importance of socio-economic characteristics of individuals or a community that determine the dissemination of information about fire incidents is critical to emergency planning and public safety. Socio-economic, demographic and cultural composition of communities plays a vital role in the success or failure of an education campaign that relies on information sharing. Effective fire prevention strategies, therefore, must address a range of social network issues in order to address the factors which facilitate or prevent risk communication within a particular community. Issues such as low socioeconomic status, social exclusion (i.e. ethnicity, English proficiency), and frequent residential mobility are significant constraints when communicating fire risk in order to reduce the likelihood of a fire. It is vital that emergency planners know these social-spatial barriers to risk communication when propagating more geo-targeted interventions to improve the effectiveness of education programs aimed at raising community awareness of residential fire risk.

This research indicates that the relationship between residential fire risk and a range of socio-spatial characteristics is not consistent throughout the Melbourne metropolitan region. For instance, in the CBD and its surrounding inner suburbs, the positive relationships were shown by the proportion of people with limited English proficiency and residential mobility, whilst the opposite was true for dwelling ownership. In the western suburbs of the Melbourne metropolitan region, the proportion of people with limited English proficiency has a positive effect on residential fire but, conversely, residential mobility has a negative effect. Consequently, when preparing intervention measures or initiatives to increase fire risk awareness, it is vital to know the local characteristics of inhabitants across different parts of the Melbourne metropolitan region.

The key task is to develop an understanding of how people in these particular areas perceive risks in the context of their own situation. Often, fire agencies develop fire safety programs and campaigns that consider only the global characteristics of a community or area; however, our findings indicate that residents have unique characteristics that determine whether they are able to receive and convey fire risk messages and information. Hence, measures to improve safety or to reduce the risk are unlikely to be accepted and implemented if the people concerned find them inappropriate or irrelevant. If fire services are to meet the needs of the community in order to change behaviour, they must first understand those needs and how the community behaves collectively. The findings suggest that fires occur amongst the "hard to reach' in the community: those who are less likely to be exposed to traditional fire intervention and safety measures. It is therefore unlikely that any single intervention will provide a solution. An integrated approach, using a variety of strategies targeted to address the needs of particular groups, is more likely to be effective. Hence, to address issues of fire safety among vulnerable groups in the community, a strong advocacy role is required to promote effective interventions and support the requirements of these groups.

Table 7-1 shows the relationship between some of the key policy milestones, the strategies and the key findings as recommendations addressing problems impacting on the practices of the fire service. In order to promote fire safety and fire prevention outlined in the Metropolitan Fire Brigades Act (1958) and the MFB annual report, the study suggests the mapping of the highest prioritized area across the region based on the current fire incidents as it is important to identify the high-risk areas in a community. It would provide a further evidence base to help develop a fire risk mitigation and prevention plan for a community.

To support the Government response regarding the establishment of an effective management of finite resources, the study suggests in-time scheduling and targeting specific communities or groups when propagating risk information. The effective fire safety education and communication can remain individuals' awareness and keep the residential fire risk as low as possible. Further, having better planning and knowledge of a community's profile would increase the confidence of fire agencies in utilizing the information to their advantage (i.e. in handling the risk within community) and optimizing the deployment of resources such as staff, and trucks.

One recommendation of this study is to place people at the centre of decision-making in regard to fire safety as outlined in the Community Resilience Framework. This study suggests that fire prevention and mitigation can be based on: the ability of residents to retain information and to memorise past fire incidents to help change behaviour; and establishing basic strategies to improve fire communication in localised clusters of higher fire risk and communication barriers driving by the contextual situations such as language, residential mobility, and other factors. The localised characteristics of community are also taken into consideration in addressing “who is at risk” and how fire agencies should deal with the uniqueness of local community when preparing and organising fire prevention initiatives.

Table 7-1: Selected Acts, policy or documentation covering fire services

Act, policy, or documentation	Year	Highlights	Recommendations from the study
Metropolitan Fire Brigades Act	1958	Instructs all fire authorities to promote fire safety and fire prevention in a bid to reduce fire risk level.	**Recommendation 1:** Mapping of the highest prioritized area across the region based on the current fire incidents as it is important to identify the high-risk areas in a community. **Reasons:** Having better planning and knowledge of a community's profile would increase the confidence of fire agencies in utilizing the information to their advantage (i.e. in handling the risk within community) and optimizing the utility of resources such as staff, trucks, etc. **Recommendation 2:** Dealing with the uniqueness of local community when preparing and organising fire prevention initiatives. **Reason:** Exploring the ability of residents to retain information can eliminate barrier to risk information diffusion and create successful risk communication or campaign **Recommendation 3:** In-time scheduling and targeting a specific communities or groups when propagating risk information. **Reasons:**
The MFB Annual Report	2015 – 2016	Delivers a set of complex and interesting challenges for emergency management sector in Victoria. There are five strategic themes: 'Always Safe', 'Improving Community Safety and Resilience', 'Valuing Our People', 'Delivering Exceptional Service', and 'Working With Others'	
Report of the Victorian Fire Services Review: Drawing a line, building stronger services	2015	Recommends that fire services adopt a shared model for the Greater Metropolitan area that allows both the CFA and the MFB working together. The model is based on enhanced integration and standard operating procedures. It would serve to strengthen fire-fighters skills, as well as improve service to the community. The second recommendation is that the fire services should develop a common understanding of the risk profile across the Greater Metropolitan area and the resources that are required to meet that risk at an acceptable level.	
Government response	2016	The government accepted the review on establishing a stronger emergency service. The response comprises three main themes: people and culture, working better together, and the effective management of resources.	
Community Resilience Framework	*On going*	Defines a framework for a modern, resilience-based emergency management system that values and understands community contribution	

Act, policy, or documentation	Year	Highlights	Recommendations from the study
		and puts people at the centre of decision-making. There are three key stages: 1) ‘mapping community resilience challenges and outcomes’; 2) ‘undertaking broad community engagement to test and discuss the key relationships between the emergency management sector, potential community resilience outcomes and challenges and the definition of resilience’; 3) ‘developing the Community Resilience Framework for Emergency Management in Victoria’	Effective fire safety education and communication can raise individuals’ awareness and keep the residential fire risk as low as possible.

7.4. ADDRESSING THE RESEARCH QUESTIONS

This study developed a stochastic model to estimate the likelihood of residential fire occurrence and to identify key urban characteristics underpinning fire patterns over time and across space. To achieve the research goal, four key research questions were developed and answered in this study.

Chapter 5 specifically addressed the first question: *How does a residential fire pattern occur over time and space*? This question has been answered through the simple descriptive statistics pertaining to residential fire dataset and the analysis of temporal patterns and spatial variability of fire datasets. In advance, the Markov chain results were also used to answer this question by having insight into local learning and memory effect.

The second research question: *Can the probability of a residential fire occurrence be predicted as a stochastic process*? was answered in Chapter 5 by applying the Markov chain. The Markov chain was used to examine the likelihood of residential fire occurrence by incorporating spatial and temporal dependence of fire risk. The model proved that the effect(s) of past fire occurrence within a neighbourhood is likely to influence the probability of fire occurrence in the future. The model was driven by the theoretical framework discussed in Chapter 2, which was based on the mechanism of local learning (i.e. the diffusion of fire risk information within the neighbourhood) and memory effect.

The third question was addressed in Chapter 6: *How do the urban characteristics impact on residential fire risk*? The Geographically Weighted Regression technique was applied to examine the relationship between fire risk and residential variables at the local level. The five key variables such as English language proficiency, dwelling ownership, residential mobility within a five-year period, dwelling density, and separate houses, were identified as having a significant influence on residential fire risk. The socio-spatial barriers to communication were discussed in Chapter 2, whereby a framework was developed to explain the residential fire risk drivers related to local social cohesion.

In Chapter 7, the fourth research question was answered: *What spatially-integrated strategies can be developed to mitigate fire risk in an urban setting*? The key strategies were developed using a fire risk-based approach including residential fire risk mapping, scheduling of fire education programs, and local intervention planning.

The primary objective of this thesis to develop a stochastic model to estimate the likelihood of residential fire occurrence and to identify key urban characteristics underpinning fire patterns over time and across space was therefore achieved.

7.5. CONTRIBUTION OF THE STUDY

The key contribution of this thesis is the development of a stochastic model which is capable of estimating the probability of fire occurrence more reliably, robustly, and accurately. In detail, the main contributions of this study are:

- The conceptualisation of residential fire risk as a stochastic process. Fire risk has not being investigated as a stochastic process to model the probability of residential fire occurrence (to increase robustness and accuracy). This study applied a stochastic process (i.e. Markov chain technique) to calculate the likelihood of residential fire occurrence. The key assumption of the stochastic process, known as memorylessness, is that the probability of fire occurrence depends on the most recent and relevant fire that has occurred within a neighbourhood.
- The integration of space, time and the context in the fire risk modelling. Key factors of spatial social barriers to risk communication which affects the likelihood of residential fire risk were identified and their spatial variability mapped at a local area level. Residential mobility, language barriers, and residential environment (such as type of dwellings, dwelling density, type of tenure) were employed in the model to investigate their influence on fire risk at the local level. A geographically weighted regression (GWR) was applied to examine how fire risk is associated with a range of keys factors on an intra-urban scale of analysis.
- This is the first time that information propagation theory has been applied in the area of fire risk modelling. Most of the spatial analyses of fire occurrence quantify the effects of neighbourhood characteristics from the perspective of spatial or urban ecology theories on fire incident behaviour, but paid little attention to the effect of past events on the subsequent rate of incidents within the local area. As discussed in Chapter 2, individuals may have a behaviour response to information about, or experience of, a fire incident in the past. They tend to change their behaviour in order to be more aware and to act to mitigate the fire risk. They also tend to be more prepared for similar incidents in the future. Experience with a hazard has long been identified as having an influence on risk perception and the use of preparedness and mitigation measures.

- This study provides the visualisation of information processing and spatial barriers to information diffusion. Spatial barriers to information propagation, retention and diffusion are identified at a local area level to help in strategic fire planning and mitigation (vital for education campaigns and interventions).

7.6. LIMITATIONS AND FUTURE RESEARCH

The approach adopted in this study has several limitations, as follows:

- Although the Markov chain model has captured space and time dependence, only one step backward (i.e. fires that occurred no longer than one month earlier) is taken into account when predicting the probability of fire occurrence in the future. Fires that have occurred in the distant past are assumed to have no significant effect whereas, psychologically, individuals or communities who have directly or indirectly experienced fire might retain the impact a bit longer after the event.
- The selection of the 2.5 x 2.5 km grid cell is problematic for the analysis of the distance decay effect on the likelihood of fire occurrence.
- Space and time dimensions have been considered simply as mathematical expressions, which can be captured as measurable properties. However, space and time are often constructed and are proxies for local learning and memory effect.
- Because the case study covered the Melbourne Metropolitan region, although the methods are general, the results indicating the relationship between fire risk and a range of spatial characteristics cannot be generalised to other areas. Further testing and validations would be required.
- The selection of spatial covariates for the model may affect specific models, whereas a broader range of spatial characteristics may cover the complexity of the social context within neighbourhoods, thereby increasing the reliability of the model.

Despite these limitations, it is suggested that the generated model provides a decision support tool which will help fire agencies with the development and implementation of policies to strengthen community resilience and the establishment of priority areas for effective policy interventions. Therefore, future research will consider:

- Taking into account a wide range of explanatory variables in addition to space and time and situated context thresholds in order to explain fire risk variability in order to strengthen the validity of the model. Different geographical and socio-economic characteristics should be taken into consideration.
- A smooth resolution at city blocks level as well. It could lead to the modifiable areal unit problem (MAUP) which highlights the need for considering an appropriate unit of scale to avoid generating contradictory results.
- The need to establish the ontology of a space-time framework which links to the psychological or cognitive aspects of human responses and spatial temporal behaviour.

7.7. FINAL CONCLUSION

The application of the Markov chain model and Geographically Weighted Regression (GWR) is a key contribution of this thesis because of the novelty of the methodology in quantifying residential fire risk which not only potentially improves the accuracy and reliability of fire risk modelling, but also enriches our understanding of behaviour associated with fire risk in relation to space, time, and situated context at the local level. The findings of this study provide new empirical evidence useful for fire agencies seeking to establish appropriate strategies to mitigate adverse impacts of fire on communities. It can also help to identify high fire risk areas and to geo-target when and where to disseminate fire safety information to increase residents' awareness of fire risk.

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Appendix A
MATLAB Coding for Markov Chain

A.1. Transition probability estimation for two-state Markov chain

```
size_grid=2982;
probstat=zeros(size_grid,2);
laplaceAlpha=1;
factor =7;
```

```
%convert to binary process
for i=1:size_grid
   for j=1:120
      if N_Fire(i,j)>0
         NBin(i,j)=1;
      else
         NBin(i,j)=N_Fire(i,j);
      end
   end
end

for i=1:size_grid
   NN(i,1)=size(find(N_Fire(i,1:factor*12)==0 & NN25(i,1:factor*12)==0),2);
   NN(i,2)=size(find(N_Fire(i,1:factor*12)>0 & NN25(i,1:factor*12)==0),2);
   NN(i,3)=size(find(N_Fire(i,1:factor*12)==0 & NN25(i,1:factor*12)>0),2);
   NN(i,4)=size(find(N_Fire(i,1:factor*12)>0 & NN25(i,1:factor*12)>0),2);

end

%Transition
PNN=zeros(size_grid,4);

%Maximum likelihood estimator
for i=1:size_grid

   PNN(i,2)=NN(i,2)/(NN(i,1)+NN(i,2));
   PNN(i,1)=1-PNN(i,2);
   if NN(i,3)+ NN(i,4)==0
      PNN(i,3)=1;
      PNN(i,4)=0;
   else
      PNN(i,3)=NN(i,3)/(NN(i,3)+NN(i,4));
      PNN(i,4)=1-PNN(i,3);
   end
   TM=[PNN(i,1) PNN(i,2);PNN(i,3) PNN(i,4)];

   probstat(i,1)=PNN(i,3)/(PNN(i,2)+PNN(i,3));
   probstat(i,2)=PNN(i,2)/(PNN(i,2)+PNN(i,3));
end
```

A.2. The n-step transition probability estimation

```
size_grid=2982;
nstep=36;
PNN=PNN25;

step=zeros(nstep,1);
P00=zeros(nstep,1);
P01=zeros(nstep,1);
P10=zeros(nstep,1);
P11=zeros(nstep,1);
```

```
for n=1:nstep
   for i=1:size_grid
      for k=1:8
         TM=[PNN(i,1) PNN(i,2);PNN(i,3) PNN(i,4)];
         TM_n=TM^n;
         P00(i,n)=TM_n(1,1);
         P01(i,n)=TM_n(1,2);
         P10(i,n)=TM_n(2,1);
         P11(i,n)=TM_n(2,2);
   end
   step(n,1)=n;
end
```

A.3. Chain Simulation for training data

```
%Variable monthly count
N = MonthlyCount;

%defining size
size_grid=size(N,1);
time_length=size(N,2);

%Defining matrix
probstat=zeros(size_grid,2);
laplaceAlpha=1;

nsample = 1000;
nfactor = 80;
step = 0.5;

diffprop=zeros(nsample,1);
diffunder=zeros(nsample,1);
diffover=zeros(nsample,1);
diffnullprop=zeros(nsample,1);
diff=zeros(nsample,1);

accuracy=zeros(size_grid,1);
accuracyprop=zeros(size_grid,1);
accuracyunder=zeros(size_grid,1);
accuracyover=zeros(size_grid,1);
accuracynullprop=zeros(size_grid,1);

meanaccuracy=zeros(4,1);
meanaccuracyprop=zeros(4,1);
meanaccuracyunder=zeros(4,1);
meanaccuracyover=zeros(4,1);
meanaccuracynullprop=zeros(4,1);

for factor = 50:1:50
   %convert to binary process
   for i=1:size_grid
      for j=1:time_length
         if N(i,j)>0
```

```
            NBin(i,j)=1;
         else
            NBin(i,j)=N(i,j);
         end
      end
   end

   for i=1:size_grid
         NN(i,1)=size(find(N(i,2:ceil((60+step*factor)*time_length/100))==0 &
         N(i,1:ceil((60+step*factor)*time_length/100)-1)==0),2);

         NN(i,2)=size(find(N(i,2:ceil((60+step*factor)*time_length/100))>0 &
         N(i,1:ceil((60+step*factor)*time_length/100)-1)==0),2);

         NN(i,3)=size(find(N(i,2:ceil((60+step*factor)*time_length/100))==0 &
         N(i,1:ceil((60+step*factor)*time_length/100)-1)>0),2);

         NN(i,4)=size(find(N(i,2:ceil((60+step*factor)*time_length/100))>0 &
         N(i,1:ceil((60+step*factor)*time_length/100)-1)>0),2);
     end
```

%Transition

```
PNN=zeros(size_grid,4);
```

%Maximum likelihood estimator

```
for i=1:size_grid
   PNN(i,2)=NN(i,2)/(NN(i,1)+NN(i,2));
   PNN(i,1)=1-PNN(i,2);

   if NN(i,3)+ NN(i,4)==0
      PNN(i,3)=1;
      PNN(i,4)=0;
   Else
      PNN(i,3)=NN(i,3)/(NN(i,3)+NN(i,4));
      PNN(i,4)=1-PNN(i,3);
   end

   TM=[PNN(i,1) PNN(i,2);PNN(i,3) PNN(i,4)];

   probstat(i,1)=PNN(i,3)/(PNN(i,2)+PNN(i,3));
   probstat(i,2)=PNN(i,2)/(PNN(i,2)+PNN(i,3));

end
```

%Chain simulation

```
X = zeros(size_grid,time_length-(ceil((60+step*factor)*time_length/100)+1)+1)

for j=1:size_grid
```

%2 states Markov Chain

```
      T = [PNN(j,1) PNN(j,2);
              PNN(j,3) PNN(j,4)];
```

%3 states Markov Chain

```
        T = [PNN(j,1) PNN(j,2) PNN(j,3);
             PNN(j,4) PNN(j,5) PNN(j,6);
             PNN(j,7) PNN(j,8) PNN(j,9)];

        transC = [zeros(size(T,1),1),cumsum(T,2)];
        n=time_length-(ceil((60+step*factor)*time_length/100)+1)+1;
        states = zeros(size_grid,n);
        states(j,1)=NBin(j,(ceil((60+step*factor)*time_length/100)+1))+1;
        rr = rand(1,n);

        for ii = 2:n
           [~,states(j,ii)]=histc(rr(ii),transC(states(j,ii-1),:));
        end

   X(j,1:n) = NBin(j,(ceil((60+step*factor)*time_length/100)+1):time_length)+
   ones(1,time_length-(ceil((60+step*factor)*time_length/100)+1)+1);
   end

   [t,khi,pval]=crosstab(X(:),states(:));
   khi_all(factor,1)=khi;
   pval_all(factor,1)=pval;

end
```

Appendix B
Simulation results

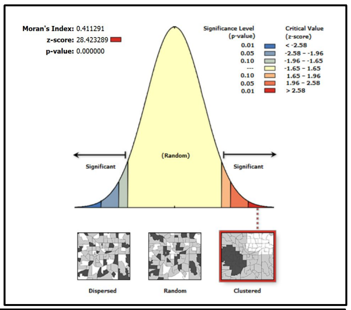
B.1. Transition probability of two-state Markov chain

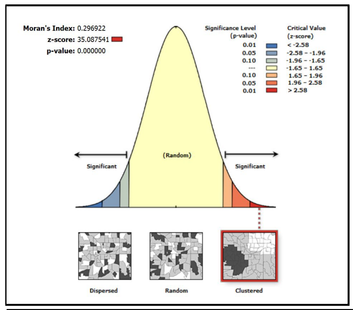
Cell_ID	SA4_NAME11	P00F	P01F	P10F	P11F
1	Melbourne - Inner South	1	0	1	0
2	Melbourne - Inner South	0.96	0.04	0.966667	0.033333
3	Melbourne - Inner South	1	0	1	0
4	Melbourne - Inner South	1	0	1	0
5	Melbourne - Inner South	0.934783	0.065217	0.9375	0.0625
6	Melbourne - Inner South	0.924528	0.075472	0.912281	0.087719
7	Melbourne - Inner South	0.965517	0.034483	1	0
8	Melbourne - Inner South	1	0	1	0
9	Melbourne - Inner South	1	0	1	0
10	Melbourne - Inner South	1	0	1	0
11	Melbourne - Inner South	0.933333	0.066667	0.9375	0.0625
12	Melbourne - Inner South	0.945946	0.054054	0.958904	0.041096
13	Melbourne - Inner South	0.931818	0.068182	1	0
14	Melbourne - Inner South	0.982456	0.017544	0.981132	0.018868
15	Melbourne - Inner South	1	0	0.980769	0.019231
16	Melbourne - Inner South	1	0	0.981132	0.018868
17	Melbourne - Inner South	0.975	0.025	0.985714	0.014286
18	Melbourne - Inner South	1	0	1	0
19	Melbourne - Inner South	1	0	1	0
⋮					
1662	Melbourne - Inner East	0.954545	0.045455	0.988636	0.011364
1663	Melbourne - Inner East	1	0	0.988506	0.011494
1664	Melbourne - Inner East	0.869565	0.130435	0.977011	0.022989
1665	Melbourne - Inner East	0.958333	0.041667	0.965116	0.034884
1666	Melbourne - Inner East	0.952381	0.047619	0.955056	0.044944
1667	Melbourne - Inner East	0.882353	0.117647	0.935484	0.064516
1668	Melbourne - Inner East	1	0	0.989583	0.010417
1669	Melbourne - Inner East	1	0	0.989583	0.010417
1670	Melbourne - Inner East	0.833333	0.166667	0.967391	0.032609
1671	Melbourne - Inner East	1	0	0.967033	0.032967
1672	Melbourne - Inner East	1	0	0.93617	0.06383
1673	Melbourne - Inner East	0.9375	0.0625	0.968085	0.031915
⋮					

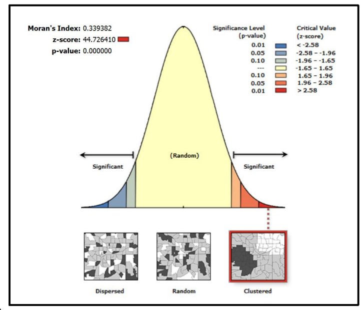
B.2. Transition probability of three-state Markov chain

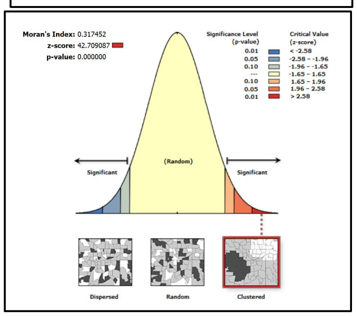
Cell	SA4_NAME11	P00	P01	P02	P01	P11	P12	P20	P21
1	Melbourne - Inner South	1	0	0	1	0	0	1	0
2	Melbourne - Inner South	0.945946	0.054054	0	1	0	0	1	0
3	Melbourne - Inner South	1	0	0	1	0	0	1	0
4	Melbourne - Inner South	1	0	0	1	0	0	1	0
5	Melbourne - Inner South	0.954545	0.045455	0	1	0	0	1	0
6	Melbourne - Inner South	0.927928	0.072072	0	1	0	0	1	0
7	Melbourne - Inner South	0.981982	0.018018	0	1	0	0	1	0
8	Melbourne - Inner South	1	0	0	1	0	0	1	0
9	Melbourne - Inner South	1	0	0	1	0	0	1	0
10	Melbourne - Inner South	1	0	0	1	0	0	1	0
11	Melbourne - Inner South	0.918182	0.081818	0	1	0	0	1	0
12	Melbourne - Inner South	0.954545	0.045455	0	1	0	0	1	0
13	Melbourne - Inner South	0.972973	0.027027	0	1	0	0	1	0
⋮									
829	Melbourne - Inner	0.761364	0.227273	0.011364	0.888889	0.111111	0	1	0
830	Melbourne - Inner	0.827586	0.16092	0.011494	0.761905	0.238095	0	1	0
831	Melbourne - Inner	0.690909	0.290909	0.018182	0.540541	0.27027	0.189189	0.578947	0.263158
832	Melbourne - Inner	0.793478	0.195652	0.01087	0.764706	0.235294	0	1	0
833	Melbourne - Inner	0.896907	0.092784	0.010309	0.8	0.2	0	1	0
834	Melbourne - Inner	0.926316	0.073684	0	0.933333	0.066667	0	0	1
835	Melbourne - Inner	0.932039	0.067961	0	0.875	0.125	0	1	0
836	Melbourne - Inner South	0.936842	0.063158	0	0.857143	0.142857	0	1	0
837	Melbourne - Inner East	0.980952	0.019048	0	0.833333	0.166667	0	1	0
838	Melbourne - Inner East	0.961905	0.038095	0	0.833333	0.166667	0	1	0
839	Melbourne - Inner East	0.961538	0.038462	0	1	0	0	1	0
⋮									

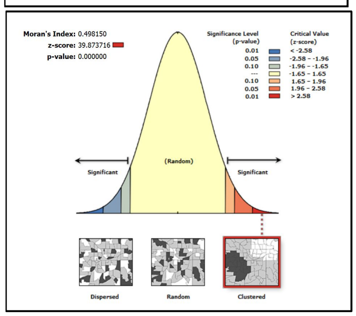
Appendix C
Spatial Autocorrelation – Moran's Index



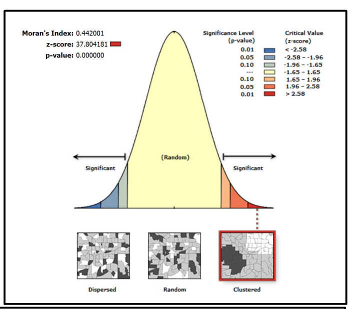


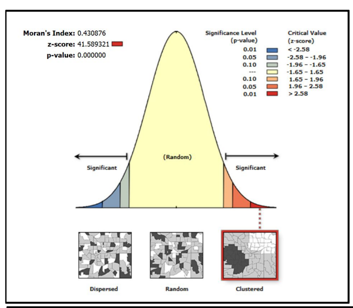


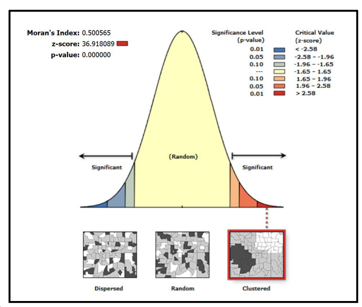


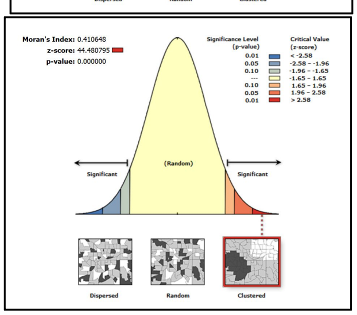


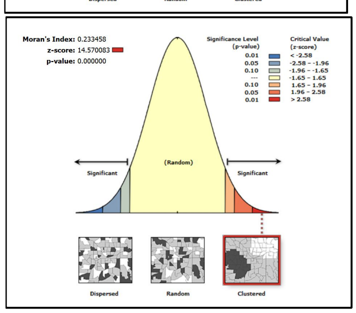
2006 2007 2008 2009 2010











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