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Modelling the Likelihood of Urban Residential Fires Considering Fire History and the Built Environment: A Markov Chain Approach

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Abstract: In this paper, we address the complex question of how the occurrence rate of residential structure fires in Melbourne city are influenced by built-environment structural forms and/or the recent history of fire incident occurred within the neighbouring areas. Numerous studies have used the socio-demographic and economic characteristics to explain the spatial variability in residential fire occurrence rates. There is however less published research that links spatio-temporal variation of residential fire occurrences with patterns and changes in the built environment, or which seeks to quantify the spatial effect of fire events on the subsequent rate of incidents within the local area.

We develop a spatio-temporal model of residential fire occurrence based on a range of spatial characteristics and past fire occurrences within neighbourhood. These spatial characteristics include the Index of Relative Socio-economic Advantage and Disadvantage (IRSAD), residential density (i.e. the relative number of dwelling per unit area), percentage of owned dwellings, percentage of privately rented dwellings, percentage of publicly rented dwellings, percentage of residents moved in the last five years, and percentage of residents moved in last year. The model is fitted to fire incidence data from Melbourne, Australia, gathered over a 10-year period. Results show that the distribution of residential structure fires across Melbourne is a complex pattern and is associated with spatially-varying indicators. The inner suburbs of the Melbourne region are more fire prone than others. Those areas have high probability of fire occurrence. This naturally follows not only from built environment and socio economic characteristics, but also correlates with recently-located residents as the tenure status in those areas. Households that have recently moved into an area, and households consisting of temporary residents, have been demonstrated in prior studies to exhibit an elevated likelihood of fire occurrence. The analysis also capture that there is a neighbourhood "memory" effect of fires, with respect to fire occurrence rates.

The results contribute to an evidence base which may be useful for emergency planners and fire agencies seeking to build appropriate strategies to mitigate fire effects on communities. It also aids in assessing and classifying areas in terms of fire occurrence likelihood, and in determining when to circulate fire safety information to residents so as to retain preparedness and awareness of fire incidents.

Keywords: *Residential fire, urban ecology, built environment, Markov chains*

1. INTRODUCTION

The analysis of urban residential fire occurrence is widely researched in recent decades because of the availability of disaggregate fire incident data for research. Numerous studies have examined the changes in spatio-temporal fire patterns and the associated fire risk. The rate of residential fire in terms of fire incident per unit area or a unit population, has been analysed by applying geographical techniques using spatial characteristics of urban space (e.g. socioeconomic indicators, structure of family, and dwelling density) as the key determinants (Chhetri et al. 2010; CorcoranHiggsBrunsdonWare, et al. 2007). These previous studies provide a useful baseline for developing methodological frameworks for the identification of the key drivers of fire incident behaviour across different cities: however, their methodological robustness can potentially be improved through greater consideration of new factors such as those associated with human learning and behaviour.

Much of the spatial analysis of fire occurrence quantifies the effects of neighbourhood characteristics on fire incident behaviour but paid little attention on the effect of past event on the subsequent rate of incidents within the local area. It is generally accepted that spatial heterogeneity may represent the existence of spatial variability of fire incidence across a large metropolitan area. This is a consequence of the differences of spatial characteristics associated with the structure of the built environment. Thus, there is a spatial dependence, meaning fire risk patterns are often spatially correlated.

From a theoretical perspective, trends in residential fire could be associated with changing urban built environment, which is dependent on the environmental conditions and situations (Sufianto & Green 2012; Yazhou, Hehe & Baojie 2010). Using geographical information systems (GIS), numerous studies have consistently demonstrated the relationships between fire incidents and the situated context within which they occur. For instance, the disadvantaged areas are often at a higher fire risk than those of advantaged areas (Chhetri et al. 2010; CorcoranHiggsBrunsdon Ware 2007; Duncanson, Woodward & Reid 2002; Wuschke, Clare & Garis 2013). Areas with high building density are also likely to experience a larger number of fires than their counterpart (Ceyhan, Ertuğay & Düzgün 2013; FEMA 2008; Jones et al. 2013; Yazhou, Hehe & Baojie 2010).

However, the risk of fire might not only be affected by environmental conditions and situations. It might also be related to how residents within a neighbourhood are linked and connected via complex social networks. If so, residential fire risk is also possibly related to (favourable and unfavourable) social interaction and exchange of information. Corcoran et al. (2011) present fire risk as a multi-scale modelling problem, ranging from larger environment to regional and neighbourhood scales through to households and the individual. They note that individual behaviour (e.g. careless use or poor supervision of cooking and heating appliances) and group behaviour (e.g. households with many children tend to let children playing at home unsupervised) can be related to fire risk. In addition, some of the studies referenced here also note that areas with low level of socio-economic status and certain family structures such as single-parent families and families with young children can have higher relative likelihoods of residential fire.

People who have strong geographical proximity or emotional connections to fire events will naturally have a higher level of information retention about the relevant hazard, yet this also implies that diffusion of information about an incident will be impeded by distance in space and in social structure (Jones et al. 2013). The intensity of information diffusion is expected to begin to dissipate once a certain distance from the event is reached, as awareness of that event thus becomes weaker beyond this distance. This is often referred as distance decay effect. If the rate of fires in a neighbourhood is affected by past fire history, this will be in line with the Geographical Law (Tobler 1970) that "*everything is related to everything else, but near things are more related than distant things*". Not only does distance tend to affect how people perceive risk and how their behaviour might change, but time is also a key factor because recalling an event becomes harder with increased time (but clearly depends upon its scale of impact, e.g., death or injury). Thus, the perception of fire risk, thus the preparedness, is also dependent on time.

If learning and awareness are to be explanatory factors for fire occurrence rates, then behaviour patterns in networks of people and the activity spaces, within which they interact, can be considered as influential as other factors. As such, the diffusion and retention of information about a fire occurrence will be subject to spatial heterogeneity of fire incidents within a given space (Kirschenbaum 2004; Kumagai, Carroll & Cohn 2004; Parker et al. 2013). The rate and intensity of information flow could be explained through community networks. Relationships and social interactions among individuals within a network have played a significant role in the recovery from a disaster and natural hazard for individuals and the community. Perception and cognition of fire risk information about experienced disasters lead some individuals to alter their risk behaviour by help developing better coping strategies and/or undertake more effective preparation against a threat of fire (Olaniran, Rodriguez & Williams ; Workman, Jones & Jochim)). Individuals who are more confident but less prepared are more likely to escalate fire risk, and thus are more vulnerable (Kumagai, Carroll & Cohn 2004).

An understanding of the fire likelihood over space and time, and having insights into residents' information perception, retention and behaviour change relating to fire, is potentially important for public safety, for emergency services planning and management, and for fire insurance market (Mueller 2015; Penman et al. 2015; Sufianto & Green 2012; Tooth 2012). Few studies have attempted to model fires as being non-uniformly distributed events occurring across time and space, even if their occurrence is somewhat predictable (Wuschke, Clare & Garis 2013). This paper therefore aims to develop a model to estimate the probability of residential fire occurrence by incorporating the spatial dependence of the location of fire occurrence and the history of prior fires within a defined neighbourhood. A Markov chain is applied to fire incident data with spatial and temporal parameters where it is assumed that fire probability at a location depends on the occurrence of the most recent fires.

This paper is organised as following. In section 2, we describe our approach for assessing fire occurrence probability by applying a Markov Chain model. Section 3 describes the result of a case study using a set of fire incidents occurring in Melbourne based on the model developed in Section 3. Finally, conclusions of this research are drawn in Section 4.

2. A SPATIO-TEMPORAL MODEL

In this paper, we use stochastic process combining Poisson regression to estimate the likelihood of fire occurrence given recent fire incidents. Consider a set of random variables $\{Y_t, t \in T\}$ defined on a given probability space and indexed by t, for $t \in T$. The set of T is often represented as time sequence of the process or location of the event, so that the set of T can be discrete or continuous. The range of Y_t generates a state space S which can be also discrete or continuous. A set of $\{Y_t, t \in T\}$ with a discrete state space S is a Markov Chain if, for sequence $t_0 < t_1 < t_2 < \cdots < t < t+1 \in T$, and values sequence $i_0, i_1, \cdots, i$ and $j \in S$, the following conditional probability holds:

$$P(Y_{t+1} = j | Y_{t0} = i_0, Y_{t1} = i_1, \cdots, Y_t = i) = P(Y_{t+1} = j | Y_t = i) = p_{ij} \tag{1}$$

where $p_{ij} \geq 0$ for all pairs $i, j \in S$ and $\sum_{j \in S} p_{ij} = 1$. The term p_{ij} is often called as the transition probability. It is a probability that event j occurs at time t given event i occurs at time $t-1$. Hence, a discrete stochastic process is practically referred as Markov Chain if the future of the set of $\{Y_t, t \in T\}$ is dependent on its present state. The transition probability in equation (1) can be arranged in matrix, denoted by $\boldsymbol{P}$, called as the transition probability matrix,

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

In our case, residential fire occurrence can be viewed as a random spatial and temporal process, so that residential fire occurrence can be formally defined as a set of random variables $\{Y_t(a),\ a \in A, t \in T\}$ in a given probability space. Consider $Z_r(a) = \{Z_1(a), Z_2(a), \cdots\}$ is the r-th zone from area a. $Z_1(a)$ is a first order zone of a (i.e. a neighbourhood of a). By proceeding the set of $\{Y_t(a),\ a \in A, t \in T\}$ follows Markov assumption, the transition probability is

$$\begin{aligned} &P(Y_{t+1}(a) = j | Y_t(a) = i_a, Y_t(Z_1(a)) = i, Y_t(Z_2(a)) = i_2, \cdots) \\ &\qquad = P(Y_{t+1}(a) = j | Y_t(a) = i_a, Y_t(Z_1(a)) = i) = p_{ij}(a) \text{, for any } a \in A, i, j \in S \end{aligned} \tag{2}$$

This is the probability of next j fires at area a given there were i_a fires occurred at area a and i_1 fires at first order zone of area a. The states of the chain are the count of fire occurrence, so that the state space may be defined in countably-infinite state space, $S = \{0,1,2,\cdots\}$. However, since residential fire is a rare event, the number of fire may be defined in countably finite state space $S = \{0,1,2,\cdots,M\}$, where M is the possible maximum number of fire throughout certain time interval.

Further, we assume a range of spatial indicators may provide effects on residential fire densities and so do fires occurred within neighbourhood in the last certain period. Consider $\{X_j(a), j = 1, \cdots, k\}$ is the set of k covariate variables which associated with spatial characteristics (e.g. socioeconomic indicator, dwelling density, proportion of nomad residents, tenure type). Let $NN_t(a) = Y_t(a) + Y_t(Z_1(a)$ is number of fires occurred at area a and its first order zone at time t. To capture multiple effect of spatial independent predictors in counting process, the Poisson regression is then used to estimate the rate parameter, so that, for any $a \in A$ and $j, i \in S = \{0,1,2,\cdots\}$, we define the transition probability from state j to state i:

$$\log\left(\frac{1-p_{ij}(a)}{p_{ij}(a)}\right) = \mu_{t+1}(a) + \gamma NN_t(a) + m(a)\exp\left(\beta_0 + \sum_{j=1}^{k}\beta_{a,j}X_j(a)\right) + \epsilon \tag{3}$$

Where ε is a random effect describing spatially unstructured variation which has the Normal Distribution with mean 0 and variance σ^2. The term of $m(a)\exp\left(\beta_0 + \sum_{j=1}^{k}\beta_{a,j}X_j(a)\right)$ is the Poisson regression. Further for each $a \in A$, the transition probability matrix of the process is

$$\boldsymbol{P} = \begin{bmatrix} P(Y_{t+1}(a)=0|NN_t(a)=0) & P(Y_{t+1}(a)=1|NN_t(a)=0) & \cdots \\ P(Y_{t+1}(a)=0|NN_t(a)=1) & P(Y_{t+1}(a)=1|NN_t(a)=1) & \cdots \\ \vdots & \vdots & \vdots \end{bmatrix} = \begin{bmatrix} p_{01}(a) & p_{01}(a) & \cdots \\ p_{01}(a) & p_{11}(a) & \cdots \\ \vdots & \vdots & \vdots \end{bmatrix}$$

3. EXPERIMENT AND RESULTS

Residential fire incident data was obtained from the Metropolitan Fire Brigade (MFB) for the period 1 June 2005 to 31 May 2015. A total of 17,849 residential fires were attended by MFB over this period. Spatial variables were derived from census data at a Statistical Area 1 (SA1) level, and provide the attribute data on the built environment and socio-economic characteristics of residents. The MFB data was processed to calculate counts of fires by SA1 per month. To test the assumption of spatial dependence of fire occurrence, Moran's Index is used. 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. Table 1 data confirms that the observations are spatially correlated (*z*-values exceed 2.58, which is 1% significance level): areas with high counts of fire occurrence are surrounded by areas also with high counts.

Table 1. Moran's Index for spatial autocorrelation test.

Year	Moran's Index	z-scores
2005	0.676823	235.48758
2006	0.780256	271.55308
2007	0.342455	119.50279
2008	0.77155	268.463
2009	0.823819	286.72329
2010	0.819341	285.1484
2011	0.859582	299.4384
2012	0.385141	134.10085
2013	0.719401	250.34855
2014	0.70113	243.9741
2015	0.634548	2207748

Figure 1 shows the mean number of days of first fire occurrence after last fire was occurred. The interval of next fire is calculated whenever a fire occurs at certain zone and certain time. From the figures, it can be inferred that Melbourne – Inner has the shortest time interval between the time of the last fire and next fire. The next fire in first zone, defined as area within radius 200 meter from fire incident, occurred on an average of 295 days (9 months); whilst others areas have about 14 month-time interval between the two consecutive fire occurrence. Figure 1 also illustrates trend of time interval across different zones. Most areas have similar trend that as the distance increase (represented by zone order), the time interval became shorter. This clearly highlighted the distance decay effect of time interval. From this, we consider in defining time lag as a time interval of nine-month period for Melbourne Inner area and 14-month period for other regions.

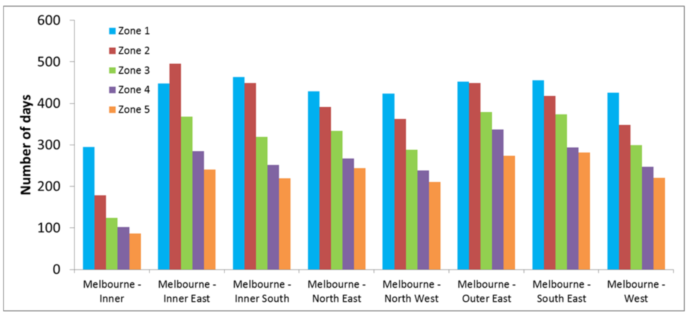


Figure 1. Number of days of first fire occurrence after last fire was occurred.

The observed transition probability of fire occurs at an area a given fires occurred at its neighbourhood including area a, $P(Y_{t+1}(a) = j|NN_t(a) = i)$, is estimated by counting the number of fire occurrence at certain time given the number of previous fires within neighbourhood divided by the total number of fire occurrence at area a. For example, one may use the rule of conditional probability:

$$P(Y_{t+1}(a)|NN_t(a)) = \frac{P(Y_{t+1}(a) \cap NN_t(a))}{P(NN_t(a))} = \frac{P(Y_{t+1}(a) \cap NN_t(a))}{\sum_{NN_t(a)} P(Y_{t+1}(a) \cap NN_t(a))}$$

The term $P(Y_{t+1}(a) \cap NN_t(a))$ is the probability of fire occurrence both in area a and its neighbourhood which fires in neighbourhood occurred first then followed by fire incidents in area a. To estimate the probability, first, we count the number of fires that satisfy $Y_{t+1}(a) = j \cap NN_t(a) = i$ for $t = 1,2,\cdots,T$. Secondly, we sum these frequencies such as $\sum_{t=1}^{T} Y_{t+1}(a) = j \cap NN_t(a) = i$. Repeat those steps for all states in S other than i and sum all these frequencies to obtain the total number of one-step fire occurrence starting in i. Finally, divide the number the second step and third step to obtain the probability.

Table 2. Parameters estimation.

	Estimate	Std. Error	z-value	p-value
Intercept	-1.75801	0.15294	-11.49500	0
residential density (Number/ha) (X_1)	-0.00526	0.00063	-8.39400	0
IRSAD Score (X_2)	-0.00050	0.00005	-10.55000	0
Percentage owned dwellings (X_3)	-0.02838	0.00148	-19.15600	0
Percentage of privately rented dwellings (X_4)	0.01041	0.00161	6.47600	0
Percentage of publicly rented dwellings (X_5)	-0.00280	0.00164	-1.71000	0.0873
Percentage of residents moved in the last 5 years (X_6)	0.02738	0.00137	19.97000	0
Percentage of residents moved in last year (X_7)	-0.00949	0.00178	-5.31800	0

The next step therefore is to develop a statistical model to estimate the probability by considering the spatial characteristics (e.g. residential density (Number/ha) (X_1), IRSAD Score (X_2), percentage of owned dwellings (X_3), percentage of privately rented dwellings (X_4), percentage of publicly rented dwellings (X_5), percentage of residents moved in the last 5 years (X_6), and percentage of residents moved in last year (X_7)). Table 2 shows the estimation of the parameters which most variables pass the 5% significance level test. In the model, the residential density (the number of buildings per hectare) is predicted to have a negative influence to the number of fire occurrences. However, from this, it cannot be concluded that low residential density per hectare corresponds to a high fire density per hectare. It does appear the case however that as the area per dwelling decreases, so does the opportunity for fire ignition, all other factors excluded. Factors such as rental and transient residents, both increasingly associated with higher density, act to give increases in fire occurrence rates with density. Considering socio-economic factors, mobility of residents has positive effect on the number of fire occurrence. It is consistent with the influence of the type of tenure indicating that rented dwellings also have contribution to elevate number of fires. The socio-economic indicator IRSAD has a small negative effect on the number of fire occurrence. This suggests that areas with low score of IRSAD – most disadvantages are more likely to have high number of fire occurrence and *vice versa*.

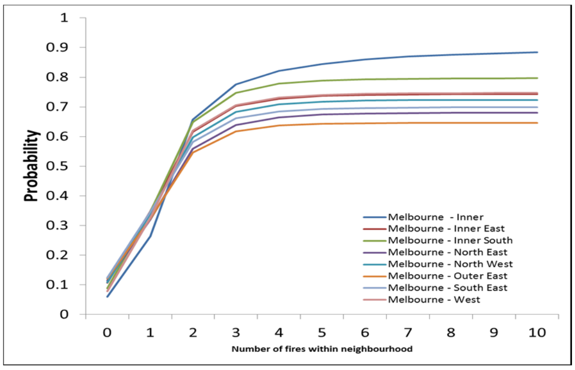
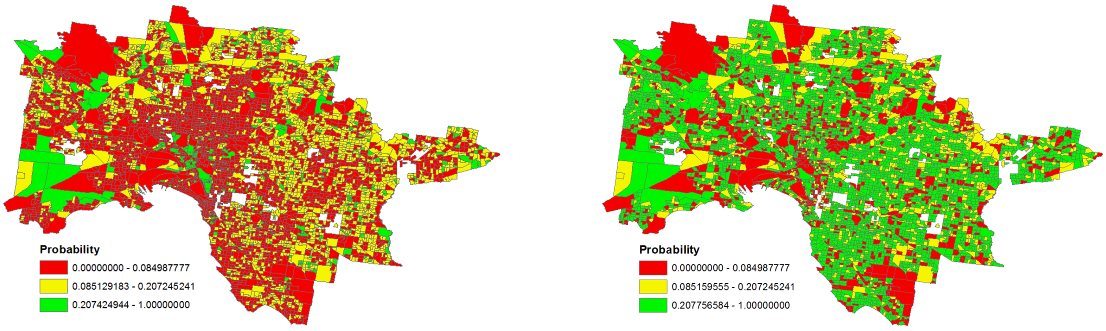


Figure 2. The transition probability of no fire incident given a number of fires within neighbourhood.

Further step is to estimate the transition probability for any SA1 and for any $j, i \in S = \{0,1,2,\cdots\}$ by using equation (3) and estimated parameters of Table 2. Figure 2 shows an example of the estimated transition probability of no fire incident given a number of recent fire incidents (i.e transition probability to state 0 from state j, for $j = 0,1,2,\cdots,15$. The result indicates that the probabilities of no fire incidents given a number of recent fire incidents are likely to exponentially increase as the number of fires within neighbourhood increases. Figure 2 also shows that when the number of fire incidents within neighbourhood is greater than three incidents, the probability of no fire incident tends to remain in constant level. It can be inferred that three of more recent fire incidents may lead residents to keep their awareness for similar incidents in the future.

Figure 3 shows an example of the likelihood map across the Melbourne region. Red colour indicates the low probability of no fire incident. In other word, the probability of fire incident will occur in the next period is high. Otherwise, green colour indicates the high probability of no fire incident; meaning that one may have high confident that there is no fire incident will occur in particular area. Figure 3(a) illustrates the probability of no fire which is given no fire incident in the past. From equation (3), one may expect that the probability of fire incident in each area depends only on its spatial characteristics (residential density, IRSAD Score, type of tenure, and mobility of residents). Figure 3(a) shows that that most areas across the Melbourne region, in particular the inner suburbs, are more fire prone which have high probability of fire occurrence (or low probability of no fire). Figure 3(b) illustrates the probability of no fire incident given a fire occurred recently within neighbourhood and shows that there is a significant different from Figure 3(a). Here, the probability of no fire incident tends to increase if there was a fire incident within neighbourhood. The likelihood of fire occurrence in most areas is changing except in some areas of inner suburbs such as Parkville, Docklands, Port Melbourne, and Southbank. The probability of fire occurrence whether there was a fire or not is likely to remain at the same. Therefore, it can be inferred that in those areas, the recent fire occurrence is likely to have no significant effect to residents to mitigate fire risk in the future.



(a) (b)

Figure 3. Map of the likelihood of no fire given no fire (a) and a fire occurrence (b) in the past within neighbourhood.

4. CONCLUSION

This research presents the preliminary findings of an analysis carried out on fire incident data for Melbourne. We developed a spatio-temporal statistical model, which enabled an empirical understanding of residential fire patterns across time and over space. First finding is the seven statistically significant spatial characteristics (e.g. residential density, IRSAD Score, type of tenure, and mobility of residents those spatial characteristics) are likely to have significant effect on the number of fire occurrence. Factor such as housing ownership and transient residents also have significant contribution to fire occurrence rates. This finding is entirely consistent with previous studies on residential fires and can be explained through urban ecology theory. The differing spatial pattern of residential fire density can be understood with respect to the consequences of human activities and changing ecological condition which in turn result vulnerability in urban areas. The second findings is whenever a fire incident occurred within neighbourhood, the probability of no fire incidents in the next certain period is likely to increase exponentially. The finding can be understood in a manner of information diffusion within neighbourhood. Information about and/or experiencing past residential fires within neighbourhood is likely to have effects and influence resident behaviour to mitigate fire risk in the future. The third finding is fire incidents occurred within neighbourhood may reduce the level of fire risk in most areas of Melbourne region except in some areas of inner suburbs, fire incidents within neighbourhood is likely to have no significant effect in reducing fire risk. Recently-located residents as the tenure status in those areas may be naturally correlated to how residents receive information about fire incident throughout certain time interval. However, this result related to information of fire risk need to be improved by linking together data on fire-related personal injuries and fire severity, to help identify whether there is an impact of spatial variables or time on injury and severity measures.

Future research will determine with confidence whether or not there is a neighbourhood "memory" effect of a fire incident. If local auto-correlation is due to the ability of residents within a neighbourhood to recall a fire event, the next step would then be to evaluate whether the strength of the effect is associated with levels of severity in terms of minor personal injury or a fatality on the extreme end of impact. The findings form part of an evidence base relating to fire occurrence rate patterns and explanatory factors, which may be useful for emergency planners and fire agencies seeking to build appropriate strategies for mitigating the potential fire impacts on communities. It also aids in the assessment and classification of areas in terms of fire occurrence likelihood risk, that in turn will help determining the best location and frequency of promoting fire safety campaigns to residents so as to retain fire preparedness and awareness of fire risk.

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REFERENCES

Ceyhan, E, Ertuğay, K & Düzgün, Ş 2013, 'Exploratory and inferential methods for spatio-temporal analysis of residential fire clustering in urban areas', *Fire Safety Journal*, vol. 58, no. 0, pp. 226-39.

Chhetri, P, Corcoran, J, Stimson, RJ & Inbakaran, R 2010, 'Modelling Potential Socio-economic Determinants of Building Fires in South East Queensland', *Geographical Research*, vol. 48, no. 1, pp. 75-85.

Corcoran, J, Higgs, G, Brunsdon, C & Ware, A 2007, 'The Use of Comaps to Explore the Spatial and Temporal Dynamics of Fire Incidents: A Case Study in South Wales, United Kingdom∗', *The Professional Geographer*, vol. 59, no. 4, pp. 521-36.

Corcoran, J, Higgs, G, Brunsdon, C, Ware, A & Norman, P 2007, 'The use of spatial analytical techniques to explore patterns of fire incidence: A South Wales case study', *Computers, Environment and Urban Systems*, vol. 31, no. 6, pp. 623-47.

Corcoran, J, Higgs, G, Rohde, D & Chhetri, P 2011, 'Investigating the association between weather conditions, calendar events and socio-economic patterns with trends in fire incidence: an Australian case study', *Journal of Geographical Systems*, vol. 13, no. 2, pp. 193-226.

Duncanson, M, Woodward, A & Reid, P 2002, 'Socioeconomic deprivation and fatal unintentional domestic fire incidents in New Zealand 1993–1998', *Fire Safety Journal*, vol. 37, no. 2, pp. 165-79.

FEMA 2008, *Residential Structure and Building Fire*, US Fire Administration.

Jones, EC, Faas, AJ, Murphy, AD, Tobin, GA, Whiteford, LM & McCarty, C 2013, 'Cross-Cultural and Site-Based Influences on Demographic, Well-being, and Social Network Predictors of Risk Perception in Hazard and Disaster Settings in Ecuador and Mexico', *Human Nature : An Interdisciplinary Biosocial Perspective*, vol. 24, no. 1, pp. 5-32.

Kirschenbaum, A 2004, 'Generic sources of disaster communities: a social network approach', *International Journal of Sociology and Social Policy*, vol. 24, no. 10/11, pp. 94-129.

Kumagai, Y, Carroll, MS & Cohn, P 2004, 'Coping with Interface Wildfire as a Human Event: Lessons from the Disaster/Hazards Literature', *Journal of Forestry*, vol. 102, no. 6, pp. 28-32.

Mueller, L 2015, 'Sanborn Fire Insurance Maps: History, Use, Availability', *The Primary Source*, vol. 26, no. 2, p. 2.

Olaniran, B, Rodriguez, N & Williams, I *Social Information Processing Theory (SIPT)*.

Parker, E, Gielen, AC, McDonald, E, Shields, W, Trump, A, Koon, K & Jones, V 2013, 'Fire and scald burn risks in urban communities: who is at risk and what do they believe about home safety?', *Health education research*, p. cyt046.

Penman, T, Nicholson, A, Bradstock, R, Collins, L, Penman, S & Price, O 2015, 'Reducing the risk of house loss due to wildfires', *Environmental Modelling & Software*, vol. 67, pp. 12-25.

Sufianto, H & Green, AR 2012, 'Urban Fire Situation in Indonesia', *Fire Technology*, vol. 48, no. 2, Apr 2012, pp. 367-87.

Tobler, WR 1970, 'A Computer Movie Simulating Urban Growth in the Detroit Region', *Economic Geography*, vol. 46, pp. 234-40.

Tooth, R 2012, 'Australian household insurance: understanding and affordability', *Sapere Research Group, Sydney*.

Workman, S, Jones, BD & Jochim, AE 'Information Processing and Policy Dynamics', *Policy Studies Journal*, vol. 37, no. 1, pp. 75-92.

Wuschke, K, Clare, J & Garis, L 2013, 'Temporal and geographic clustering of residential structure fires: A theoretical platform for targeted fire prevention', *Fire Safety Journal*, vol. 62, Part A, no. 0, pp. 3-12.

Yazhou, J, Hehe, G & Baojie, L 2010, 'Urban fire risk evaluation of Xuzhou city based on GIS', paper presented to Geoinformatics, 2010 18th International Conference on, 18-20 June 2010.