Modeling Spatial–Temporal Dynamics of Urban Residential Fire Risk Using a Markov Chain Technique

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Abstract This article applies a Markov chain method to compute the probability of residential fire occurrence based on past fire history. Fitted with the fire incidence data gathered over a period of 10 years in Melbourne, Australia, the spatially-integrated fire risk model predicts the likely occurrence of fire incidents using space and time as key model parameters. The mapped probabilities of fire occurrence across Melbourne show a city-centric spatial pattern where inner-city areas are relatively more vulnerable to a fire than outer suburbia. Fire risk reduces in a neighborhood when there is at least one fire in the last 1 month. The results show that the time threshold of reduced fire risk after the fire occurrence is about 2 months. Fire risk increases when there is no fire in the last 1 month within the third-order neighborhood (within 5 km). A fire that occurs within this distance range, however, has no significant effect on reducing fire risk level within the neighborhood. The spatial–temporal dependencies of fire risk provide new empirical evidence useful for fire agencies to effectively plan and implement geo-targeted fire risk interventions and education programs to mitigate potential fire risk in areas where and when they are most needed.

Keywords Australia · Markov chain · Melbourne · Residential fire risk · Spatial–temporal analysis

1 Introduction

Residential fire (called simply fire hereafter) is a fire that has occurred in residential property only. Fire risk, in general, is the probability of a fire occurrence and its potential consequences (for example, 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, often exhibited by in situ behavior such as alcohol drinking habits and 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 (Leth et al. 1998; Jennings 2013; Clark et al. 2015). Fire risk, therefore, is difficult to examine as it is driven by a multitude of interwoven factors.

Space and time are the two key, yet inadequately understood, dimensions of fire risk. Space and time are vital in shaping the ability of people to recall interactions, episodes, or events that occur in the recent past and/or directly within their neighborhood. This cognitive ability to remember and recall information begins to dissipate with time. Time is thus one of the key drivers of information retention and recall. This is because memory is heavily dependent on the frame of time. Space and time therefore are fundamental drivers of the perception and awareness of fire risk. Prevention of potential threats from fire and preparedness to help mitigate fire risk is heavily dependent on this awareness.

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Space and time dimensions are not only vital for theory building, but also are critical to addressing key policy questions. In order to mitigate fire risk, it is important for fire agencies to know the likely impact of time on fire risk in areas with a fire or no fire within a certain period. Emergency planners would also benefit from knowing the effect of distance beyond which its impact on fire risk begins to diminish. This augmented knowledge would help in the planning and implementation of education programs in areas where and when they are needed. There is currently limited empirical research that estimates the effect of space and time on fire risk. This study therefore argues that residential fire risk could be estimated through the historical fire incident patterns whereby space and time serve as model parameters to estimate fire risk as a stochastic process (that is, a Markov chain). The commonly held assumption is that the likelihood of a fire within a certain distance and time is affected by when a fire has occurred in a neighborhood. Hence, the phenomenon of fire occurrence is space and time dependent. The historical specificities of fire incidents provide the situated context to capture spatial and temporal dependencies to enrich the likelihood estimations of fire risk. This study builds on previous works by Corcoran et al. (2007b), Corcoran and Higgs (2013), and Chhetri et al. (2010), and models spatial and temporal dependencies of fire risk as a stochastic process by analyzing recent historical fire data using the Markov chain approach.

This article is organized into six sections. Section 2 builds a theoretical framework to examine the role of space and time in shaping residential fire risk. The research methodology adopted in this study is presented in Sect. 3, followed by the results of the case study conducted in Melbourne in Sect. 4. Section 5 discusses policy implications of the key findings. The final section concludes this study along with setting up an agenda for future research.

2 Literature Review

Modeling residential fire risk is theoretically complex and methodologically challenging. Various definitions and theoretical frameworks were therefore developed to model fire risk from a range of perspectives. Špatenková and VIRRANTAU (2013) define fire risk as the probability of a fire incident occurrence and its consequences. Similarly, Xin and Huang (2013) consider fire risk as the product of the probability of fire occurrence and the expected consequence such as physical loss and/or psychological damage. Chuvieco et al. (2010) used the term “fire risk” to denote the chance of fire ignition as the result of the presence of a causative agent.

Fire risk has been quantified using a range of measures such as the count of fire incidents per unit (Duncanson et al. 2002; Corcoran et al. 2011) and fire rate (Chhetri et al. 2010; Corcoran and Higgs 2013; Špatenková and VIRRANTAU 2013). Rohde et al. (2010) and Lin (2005) have quantified fire risk in terms of the probability of fire occurrence. In each of these definitions, the key elements of fire risk are the occurrence of fire itself, the hazard that causes fire, the expected occurrence of the fire, and the consequences (property damage, psychological harm, or financial loss). Despite these attempts, there is no single universally defined framework of fire risk that fits all different theoretical perspectives and methodological approaches. In this study, fire risk is presented as the likelihood of a fire as a function of past fire history. It is a situation that involves exposure to areas of elevated fire risk. Presence of hazards or the consequences of fire are excluded from the scope of this study.

Over the last 2 decades, a number of advanced statistical methods (Duncanson et al. 2002; Corcoran et al. 2007a; Chhetri et al. 2010; Wuschke et al. 2013) have been applied to quantify residential fire risk. They have modeled and mapped spatial–temporal fire patterns and established their association with individual or neighborhood characteristics. However, the processes and patterns of how fire events occur in time and over space, and the way they influence fire risk, are largely under investigated. It is important to know how past fire events within a local neighborhood influence the subsequent occurrence of fire incidents. Table 1 lists the seminal studies and analytic tools/methods applied to model residential fire patterns/risk. Most of these studies conclusively established the association between fire risk and dwelling-related properties (for example, material combustibility and presence/absence of a smoke detector), sociodemographic and economic attributes (for example, socioeconomic status, education levels, family type, and housing tenure), and behavioral characteristics (for example, smoking habits, alcohol consumption, and attitude). However, none of these studies have explicitly incorporated both space and time as modeling parameters in fire risk estimation. Most previous studies treated space and time as independent dimensions in their models. Residential fire risk was modeled by considering either spatial or temporal dependence as a function of neighborhood characteristics or environmental conditions. The effect of past events on the subsequent fire incidents at a local area level is yet to be modeled. There is therefore a relative paucity of studies that allow simultaneous integration of space and time in fire risk modeling.

From a theoretical perspective, fire risk might potentially be affected by the ways people interact within a neighborhood or in a local community. The diffusion of information theory, introduced by Rogers (1962), has

Table 1 Key studies in residential fire risk modeling

Modeling approach/ method	References	Objective	Dependence		Spatial variation parameters	Temporal variation parameters	Case study
			Space	Time			
Descriptive statistics	Corcoran et al. (2011)	Fire risk-associated factors	Yes	–	Socioeconomic status, disadvantaged/advantaged areas, calendar events, weather	–	
Descriptive statistics	Duncanson et al. (2002)	Fire risk-associated factors	Yes	–	Socioeconomic status, ethnicity, education, tenure	–	
Hotspot analysis	Wuschke et al. (2013)	Fire patterns	Yes	–	Crime occurrence	–	Canada
Logit model	Goodsman et al. (1987)	Fire risk-associated factors	Yes	–	Family structure, building type	–	
Regression	Corcoran et al. (2007b)	Fire risk-associated factors	Yes	–	Socioeconomic status, disadvantaged/advantaged areas	–	
Regression	Chhetri et al. (2010)	Fire risk-associated factors	Yes	–	Disadvantaged/advantaged areas, ethnicity, family structure	–	Australia
Regression	Corcoran et al. (2011)	Fire risk-associated factors	Yes	–	Disadvantaged/advantaged areas, family structure, car ownership, education, tenure, building status, ethnicity	–	UK
Point process and Geographically Weighted Regression (GWR)	Špatenková and VIRRANTAUŠ (2013)	Fire risk-associated factors	Yes	Yes	Population, building type, socioeconomic status, education, family structure	Hourly	Finland
Poisson process	Lin (2005)	Fire probability in building	Yes	–	Building type	–	Taiwan, China
Beta distribution	Rohde et al. (2010)	Fire probability	Yes	–	Number of buildings, number of inhabitants	–	
Bayesian network	Cheng and Hadjisophocleous (2009)	Fire probability in building	Yes	–	Building structure	–	
Bayesian network	Hanea and Ale (2009)	Fire scenario	Yes	–	Location, structure, fire system	–	Netherland
Bayesian network	Cheng and Hadjisophocleous (2011)	Fire probability in building	Yes	–	Building structure, heat, fuel	–	
Bayesian network	Matellini et al. (2013)	Fire probability in building	Yes	–	Fire type, fire system	–	UK
Bayesian approach	Rohde et al. (2010)	Fire probability	Yes	–	Number of buildings, number of inhabitants	–	Australia
Kernel density estimation (KDE)	Corcoran et al. (2007b)	Fire patterns	Yes	–	Socioeconomic status	–	
Ripley's K function	Ceyhan et al. (2013)	Fire patterns	Yes	–	Residential property	–	Turkey
Geodemographic analysis	Corcoran et al. (2013)	Fire patterns	Yes	–	Population density	–	Australia

served as a foundation for mapping the communication process that involves interpersonal communication or the exchange of information between two or more individuals.

Effective communication among members of a local commune often influences their views and perceptions (Reed et al. 2010) and results in quicker diffusion of

information within local networks. Successful risk communication can lead to improved fire safety behavior that in turn affects fire prevention and mitigation (Plough and Krimsky 1987). However, the mechanism through which information about fire risk is transmitted and communicated among individuals, groups, and institutions is affected by the space and time relationship (Plough and Krimsky 1987).

Spatial proximity is a key driver of dissemination of information about fire risk and preventive measures (Clark et al. 2015; Ma 2015). Individuals are more likely to be better physically connected and socially linked to others when they are geographically close (Hagerstrand 1968). This is because people create a local network, improve social cohesion, and build trust within their neighborhood. This local commune then becomes a conduit for information sharing and exchange of ideas, knowledge, and experiences. 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. This increased awareness helps people prepare better for or prevent the threat of potential or real fire (McGee et al. 2009; Clode 2010). The relationship between individuals within a circle of acquaintances within a geographic milieu therefore plays an important role in the diffusion of fire risk information. This is often referred to as the “neighborhood effect.”

The perception of fire risk is also affected by the time dimension. That is the ability of individuals to remember, recall, and react to past fire incident over time (Clode 2010). Recall ability involves the time from when an individual first receives the information, to processing a decision to accept or reject the data, through to implementing or confirming a decision. Therefore, time can be constructed as time interval, measured from the initial diffusion process starting to the acceptance or rejection of the information (Hagerstrand 1968).

Local learning and the ability to recall information in shaping the perception of fire risk at an aggregate level (for example, a geographic unit) are difficult to formulate and model. An alternative is to model fire risk as a function of space and time that could be treated as proxies to reflect local learning within a neighborhood and the ability to recall information from past experiences. Space delineates the boundary, which shapes spatial interactions within the local community. Space thus provides the place for social interaction that in turn influences the process through which risk is communicated and perceived. Social and economic structures undoubtedly underpin “what” occurs in a place; but “how” it occurs (and in what form) is largely determined by spatial relations that influence the processes and the nature of social interactions (Simonsen 1996). Space can be constructed as a physical entity at

different geographic scales (Pries 2005) or as a socially constructed entity, although time lag can be represented as a period between two related or unrelated events within a local area. It can be defined either in discrete (for example, day, week, month, year) or continuous (for example, time interval) terms. Space can be partitioned into discrete or fuzzy zones using a range of distances. The magnitude of spatial interactions decreases with distance away from the focal area. Time lag is represented as a period between two fire occurrences expressed as a discrete unit (for example, weekly, monthly).

In this study, a Markov chain-based framework was developed that allows spatial and temporal dependence to be theorized and quantified to reflect neighborhood and “memoryless” effects. The premise of the Markov process is that the next state is entirely based on its current state, which then determines the diffusion of fire risk over time and space. In other words, the likelihood of a fire at a location is highly dependent on how much time has elapsed after the last fire in that location. Figure 1 illustrates the interaction between time, space, and fire in a three-dimensional frame. In the space dimension, when a fire occurs in an area, the information about that fire is first transmitted to its immediate neighbor and then diffuses across a larger region. Since the intensity and magnitude of information diffusion diminishes with distance at a certain distance decay rate, only those fire incidents that occur within a certain threshold distance from location s (that is, neighborhood of s) would make more impact on residents’ perception of fire risk. Scherer and Cho (2003) also argued that distant objects or phenomena have limited effects such that the influence of the focal object on others beyond its neighborhood is relatively small. In the time dimension, 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 occur in recent time. Given that a residential fire occurred at time $t - k$ for $k = 1, 2, \dots$, only those residential fires that occurred at $t - 1$ potentially influence individuals’ perception of fire risk. The Markov process then follows, which is the probability that a fire incident following on from another depends on space and time dimensions.

Despite the existence of a large number of studies on modeling fire risk, the estimation of fire risk, as a Markov chain process with space and time dimensions, is hardly explored in the existing literature. Although fire risk depends on the spatial characteristics of the situated context, yet it can also be considered simultaneously as a continuous process of change in space and time. This improved understanding of the neighborhood effect as a spatial process and the memory effect as a temporal process arguably can provide deeper insights into the

Fig. 1 A spatial–temporal three-dimensional framework for modeling fire risk

complexity of the perception of fire risk. To improve the predictive ability of fire risk models, the Markov chain is used to model fire risk with space and time as surrogates for local learning and the ability to retain information about fire. Using the fire incident data, time is structured as discrete units (month, year); whilst space is organized as zones (with a radius of 2.5 km). The Markov chain technique is applied to examine the probability of fire occurrence by allowing for essential statistical dependence in space and time lag. The Markov chain is used to model sequential dependencies that influence the spatial dynamic of fire risk as a geographic phenomenon.

3 Research Methodology

This section provides an introduction to the study area and presents details on the research methodology adopted in this study, including fire incident data and the Markov chain model.

3.1 Study Area

Our fire risk model is developed for Melbourne—the capital of the state of Victoria, and the second most populous city in Australia with about 4.88 million residents (ABS 2016). Over the last 2 decades, the geography of Melbourne has been significantly transformed in terms of both the built-up environment and the increased cultural diversity of its inhabitants. Over the last decade, the restructuring of Melbourne’s urban systems has been driven by urban consolidation and higher dwelling-density developments within and around designated key activity centers and Transit-Oriented Development (TOD) nodes. This urban transformation poses new challenges for the management and delivery of emergency services in inner and outer suburbia (Dittmar and Ohland 2012; Searle et al. 2014). The fire risk patterns in high-density areas in a compact city model might be different to those exhibited in a single-family, low-density housing environment.

The perception of fire risk might vary across different sociocultural groups inhabiting different parts of urban

spaces. Hence, risk mitigation strategies would be more effective to enhance education programs and awareness campaigns if they are area specific and time dependent. The analysis of historical fire incident data is therefore crucial in producing empirical evidence to drive systemic change in the already-established regulatory environment in order to help improve community safety and develop resilience to fire threats.

3.2 Fire Incident Data

This study has used fire incidence data that represent a period between March 2006 and May 2015. The residential fire data were taken from all official fire incident reports of 47 fire stations across 26 Local Government Areas within Melbourne. Since 2005, the residential fire database is well maintained by the Metropolitan Fire Brigade (MFB) for accuracy and reliability. However, the data series from March 2006 to May 2015 were used because there is an anomaly for some data such as September 2005, January 2006, and February 2006. The fire incident data contain georeferenced information about 17,484 fires, which include location, time of incident, cause of fire, types of building, alarm level, number of fatalities, and fire origin. Additional information has been added to this database such as distance from the city center and distance from the nearest fire station. The fire data have been cleared from other types of fire such as bushfire, vehicle fire, false alarm, and others such that it only contains records of residential fire.

Table 2 shows the distribution of residential fires in the Melbourne metropolitan area from March 2006 to May 2015 with inner and west Melbourne having a higher risk of fire. In Melbourne's inner city districts 10,760 fires occurred, followed by 2883 fires in northern suburbs, 2282 fires in western suburbs, and 1923 in eastern suburbs.

There were a total of 35 fatalities in 10 years. The majority of fires occurred in one-family units (58.5%) and

Table 3 Characteristics of residential fires in the Melbourne region, March 2006–May 2015

Variable	Number of fires	Percentage (%)
Living unit type		
One-family units	10,444	58.5
Three to six living units	905	5.1
Seven to 20 living units	1589	8.9
Over 20 living units	2790	25.6
Apartment, flats	310	1.7
Area of fire origin		
Kitchen	8005	44.8
Bed room	1529	8.6
Lounge area	855	4.8
Laundry room	551	3.1
Garage	445	2.5
Month of fire		
June–August (Winter)	4804	26.9
September–November (Spring)	4408	24.7
December–February (Summer)	4245	23.8
March–May (Autumn)	4392	24.6
Time of fire		
6 p.m.–5 a.m. (night)	9640	54
6 a.m.–5 p.m. (day)	8206	46
Weekend fire	5470	31.3
Fire with fatalities	35	0.002

residential buildings with over 20 living units (25.6%). Apartments were less likely to be affected by fire (1.7%). Forty-four percent of all residential fires started in the kitchen; 8.6% and 4.8% occurred in the bedroom and living room, respectively. Most residential fires occurred either in winter (26.9%) or summer from December to February (23.8%). Evening is a crucial time with 54% of fires occurring at night. Thirty-one percent of fires in Melbourne occurred during the weekend (Table 3).

Table 2 Residential fires in Melbourne region, March 2006–May 2015

Area (statistical area level 4)	Area (km ²)	Total living units	Frequency of fire through 10 years	Number of fires per 1000 living units	Number of fires per km ²
Inner	113.1	344,022	6649	19.3	58.8
Inner East	130.8	260,119	2005	7.7	15.3
Inner South	116.9	275,798	2106	7.6	18.0
North East	167.8	240,569	1736	7.2	10.3
North West	120.1	143,249	1147	8.0	9.6
Outer East	110.7	126,117	924	7.3	8.3
South East	91.8	127,569	999	7.8	10.9
West	161.3	216,652	2282	10.5	14.1

3.3 Method: The Markov Chain Model

The Markov chain model was used to estimate the likelihood of residential fire. The study area was divided into a finite sum of homogenous sized grid cells. The advantage of the grid approach is its 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 cell size 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 being studied. For example, for 2.5×2.5 km grid cells, about 28% (849 out of 2982) of the grid cells contained zero values, whilst for 1×1 km sized grid cells, 61% contained zeros. Zero value indicates, no fire incident within a cell during the study period, or land parcels allocated to nonresidential purposes such as industrial/commercial activities or parks and reserves. This study used 2.5×2.5 km sized grid cells, not only by considering the zero observations but also by adopting what most residents of an area might commonly perceive to be their neighborhood within which they access vital infrastructure and amenities, such as train stations, shopping centers, and entertainment.

Spatial-temporal relationships were established by demarcating neighborhoods for each of the cells across the grid. As shown in Fig. 2, a neighborhood is delineated by identifying cells, which are spatially adjacent to the focal cell. Thus, the neighbors—that is a set of eight cells surrounding it—are referred as the “neighborhood in space.” Neighborhood operation was implemented across a raster grid, one cell at a time. In each cell, fire risk is computed as a function of its neighborhood. The neighborhood function is then extended in the temporal dimension to create the “neighborhood in space and time” (Fig. 2). This neighborhood operation is then temporally integrated to scan the

presence or absence of one or more fires with the temporal resolution of a month.

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

The set of values of $Z_s(t)$ 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 neighborhood. The number of fires that have occurred in the past within a neighborhood also affects fire risk, which is modeled using a 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, $\{Z(s, t)\}$ indicates the presence of a residential fire at a cell s , $s = 1, \dots, n$, at a time t , $t = 1, \dots, T$, so that the vector $Z(t) = (Z_1(t), \dots, Z_n(t))'$ represents a map describing the presence of fires at time t . By assuming the fire occurrence sequence is captured through a stochastic process model for $Z(t)$ that follows a first-order Markov chain, the conditional probability is then defined as $P(Z(t+1)|Z(t), \dots, Z(1)) = P(Z(t+1)|Z(t))$. It is the probability that a fire occurring at time $t+1$ given historical fire incidents (that is, $Z(t), \dots, Z(1)$), 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

Fig. 2 Modeling neighborhood in three-dimensional space and time relationships to determine fire risk

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

The probability in Eq. (1), in other words, 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, that is, $Z_s(t+1)$, depends only on the presence of fire $Z(t)$.

3.3.1 The One-Step Transition Probability

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

$$P(Z_s(t+1) = j | Z(t) = i) = p(s, t) \quad (2)$$

This is the probability of fire occurrence at a location s at time t given the occurrence of a fire event within its neighborhood at time $t-1$. In this study, one step was delineated by 1 month. Thus, time step is referred on a monthly basis. If one-step transition probabilities $p(s, t)$ are independent of t , a Markov chain is called 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. It is known as the one-step transition probability matrix, denoted as $P(s)$:

$$P(s) = \begin{bmatrix} p_{11}(s) & p_{12}(s) & \dots & p_{1k}(s) \\ p_{21}(s) & p_{22}(s) & \dots & p_{2k}(s) \\ \vdots & \vdots & \dots & \vdots \\ p_{k1}(s) & p_{k2}(s) & \dots & p_{kk}(s) \end{bmatrix} \quad (3)$$

where k represents the number of states (for example, $k = 2$ 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 changing from an existing state to another state.

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

$$\hat{p}_{ij}(s) = \frac{n_{ij}(s)}{N_i(s)} \quad (4)$$

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 neighborhood of s .

In practice, the MLE method is applied as follows: (1) Count the frequency of states that satisfy $Z_s(t+1) = j \cap Z_s^*(t) = i$ for $t = 1, 2, \dots, T$ with $Z_s^*(t)$ represents state within the neighborhood of location s ; (2) Add these frequencies thus: $\sum_{t=1}^T Z_s(t+1) = j \cap Z_s^*(t) = i$; (3) 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 ; and (4) 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} be a residential fire sequence at grid cell #1503 (a cell located in Melbourne's Inner East region). The transition probability of current states of fire given the previous state of no fire

Fig. 3 Pattern diagnostic plots for the number of residential fire occurrences, April 2006–May 2015, in Melbourne, Australia

Table 4 Goodness-of-fit test for training data

Models	70%	75%	80%	85%	90%
<i>Two-state Markov chain</i>					
χ^2	0.5044	0.2190	1.3349	0.9371	0.6154
<i>p</i> value	0.4776	0.6398	0.5130	0.3333	0.4328
<i>Three-state Markov chain</i>					
χ^2	3.7427	3.0929	2.6056	2.0249	1.5319
<i>p</i> value	0.9967	0.9966	0.9957	0.9916	0.980

(denoted as p_{01}) is then calculated by summing 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 (that is, $Z_s^*(t) = 0$),

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

The result above indicates that the probability of fire occurrence at grid cell #1503, if there was no fire incident in the last 1 month within its neighboring grid cells, is equal to 0.375. 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:

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

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

3.3.2 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. But one might be interested in estimating the probability of transitioning from one state to another in more than one step. The theory and details of a transition probability can be found in several studies (Billingsley 1961; Ching and Ng 2006; Iosifescu et al. 2010; Bai and Wang 2011; Çinlar 2011; Pinsky and Karlin 2011; Castañeda et al. 2012). 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.

$$p_{ij}(s)^{(k)} = P(Z_s(t+k) = j | Z(t) = i) \quad (5)$$

and the associated k -step transition matrix is

$$P(s)^{(k)} = \{p_{ij}(s)^{(k)}\} = P^k, \quad \text{for } k = 1, 2, \dots \quad (6)$$

When the number of 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 study, we calculated the k -step transition in order to examine the month-to-month probability of fire occurrence.

Fig. 4 Estimated probabilities of fire occurrence given no fire incidents within the designated neighborhood using a two-state Markov chain in Melbourne, Australia

Fig. 5 Estimated probabilities of fire occurrence given at least one fire incident within the designated neighborhood using a two-state Markov chain in Melbourne, Australia

4 Results and Key Findings

This section provides the results of the estimation of residential fire risk using the Markov chain method and the key findings that are related to the space and time context of fire risk.

4.1 Spatial Autocorrelation

Initially, to test the assumption of spatial independence across the region, Moran's I index was calculated. The calculated value of Moran's I is 0.38 with z -score of 86.88. The results indicate that the spatial distribution of high fire incident values and/or low values in the dataset is more spatially clustered than would be expected if underlying spatial processes were random ($p = 0.001$). In other words, high fire risk areas are surrounded by neighbors with high fire risk.

4.2 Time Series Analysis

To test the stationarity of fire occurrence time series, the diagnostic plots of time series consisting seasonality, trend, and pattern were used. Figure 3 shows month-to-month variations from April 2006 to May 2015. The plots indicate that the residential fire occurrences seem to be relatively steady throughout the year.

4.3 Model Development and Validation

In order to determine whether the estimations of fire risk are accurate, acceptable, and valid, model validation was conducted. A data mining approach was adopted whereby the dataset was divided into two parts: training data and test data. The training data was used to fit the Markov chain model, that is, to estimate the transition probability. A Chi squared goodness-of-fit test is used. For each grid cell, 70% 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 (August 2012–May 2015) as test data and then the process was repeated by selecting 75–90% of the data as training data. The objective here is to gauge the effect of sampling bias on the result obtained. The results indicating the prediction accuracy are depicted in Table 4.

The p value showed in Table 4 indicates the degree of significance in the results. Customarily, a p value of 0.05 or less indicates strong evidence against the model, that is, 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. For further analysis, the study used 80% of the data to calculate the parameters of the Markov chain model.

4.4 Fire Occurrence Probability Levels

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

Fig. 6 Estimated probabilities of fire occurrence given at least two fire incidents within the designated neighborhood using a three-state Markov chain in Melbourne, Australia

Fig. 7 Month-to-month probability of fire occurrence in Melbourne's urban landscape depending on recent fire history

chain: (1) starting with no fire incident in the past; and (2) starting with at least one fire incident in the past.

The second case is the three-state Markov chain: (1) starting with no fire incident in the past; (2) starting with one fire incident in the past; and (3) starting with at least two fire incidents that occurred in the past within a neighborhood. The following presents the results of these two cases.

4.4.1 Two-States Markov Chain Model

Figure 4 shows the probabilities of the two-state Markov chain given no fire in the immediate past within the neighborhood. Lower probabilities are depicted with light

yellow color and higher probabilities are shown in red. The natural break method was used to classify data to differentiate spatial variability in the levels of fire probability. Statistical Areas (SA) 3 and 4 are geographical areas designated by the Australian Bureau of Statistics (ABS) to create a standard framework for census data analysis at regional city level and state/territory level, respectively. The fire risk levels show a city-centric pattern (Fig. 4). In the case with no fire in the immediate past, 25 grid cells or 1.2% of cells across Melbourne are at a high fire risk (0.349–1), 4.0% are at medium to high risk (0.174–0.348), 13.3% are at medium risk (0.090–0.173), 36.9% are at low to medium risk (0.043–0.089), and the remaining 44.6% are at low fire risk (0.009–0.042). The inner city areas are

Fig. 8 The distance-based probability of fire occurrence in Melbourne if the given starting state (dotted line) is no fire incident occurred within the neighborhood; (dashed line) a fire incident occurred within the neighborhood; and (solid line) at least two fires occurred within the neighborhood

at a higher fire risk with values ranging between 0.349 and 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 neighborhoods in the immediate past (Fig. 5), the probability of fire occurrence is more spatially dispersed across the region. Nonetheless, inner city, especially the southern part of the inner city, still has an elevated fire risk. Compared with the first case, 2.2% of Melbourne are categorized as at high fire risk, 8.2% are at medium to high risk, and 8.6% are at medium fire risk. The remaining cells are at low fire risk (80.9%). More areas are at low fire risk when only one fire occurred in the immediate past within the neighborhood.

4.4.2 Three-State Markov Chain Model

To examine the effect of the number of fires occurred in the immediate past within neighborhoods, the three-state Markov chain model was developed. By using a method similar to the 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 neighborhood in the last 1 month, similar results to those shown in Fig. 4 were produced. In the second case of one fire, a dispersed fire risk pattern also has similar pattern to the second case of the two-state Markov chain shown in Fig. 5. Based on the same classification scheme, 2.7% of cells in Melbourne are at a high fire risk level, 8.9% are at medium fire risk, and more than 77.6% are at a low level of fire risk. Inner city areas are at a higher risk when compared to other suburbs given one fire within the neighborhood in the last 1 month.

In the third case, given at least two fires within a neighborhood, only some areas in the inner city are

classified in the high fire probability level. Less than 1% of cells is at a high fire risk, while the remaining cells are at a low level of fire risk (Fig. 6).

The results of the models were aggregated to the administrative unit level to make the analyses more relevant for policy making and strategic planning. Fire probabilities computed for grid cells were aggregated at the Statistical Area Levels 3 and 4. The Aggregate function of ArcGIS resampled fire probability input raster to a coarser resolution (that is, SA3 and SA4) based on a specified aggregation operator—Mean. The administrative boundaries (polygons) were intersected with the grid to compute the mean value of probabilities within each of the Statistical Areas.

Table 5 shows the summary of the mean of probabilities across statistical areas based on two-state and three-state Markov chains. The results indicate similar spatial fire risk patterns to those illustrated in the grid model. The ANOVA was used to test whether there are significant effects of past fire occurrence within the designated neighborhood in the last 1 month across the grid cells. Two factors were employed for this test: the three cases of the probability (starting with no fire, one fire, and at least two fires in the immediate past) and Statistical Areas. In the case of a two-state Markov chain, the F value of 1.87 for the variability test within subregion (p value 6×10^{-47}) indicates a significant difference in the probabilities of fire occurrence between the subregions, while F value of 35.99 (with p value $= 2.3 \times 10^{-9}$) indicates a significant difference in the probabilities of fire occurrence between the cases.

The three-state Markov chain shows similar results. F values of 2.3 and 136.2 for the variability test within the subregions and between the three cases indicate that there is a significant difference in the probability of those cases. From the test, it can be concluded that with the 95% confidence interval, there is a significant difference in the probabilities between the subregions and between the cases. The result also affirms that the probability of fire occurrence with no fire within the vicinity of neighborhood is relatively higher than both for areas with one fire and at least two fires in the last 1 month. Furthermore, this indicates that fire occurrences within the neighborhood, especially one with a greater number of fires in the last 1 month, are more likely to contribute to the reduction of the probability of a fire in Melbourne.

4.5 Month-to-Month Variation in Fire Probability Levels

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 (that is, from no fire to a fire). This transitioning of state could occur on a daily,

Table 5 Mean of probabilities across subregion based on two-state Markov chain and three-state Markov chain models

Subregion	Level	Number of grid cells	Two-state Markov chain			Three-state Markov chain			Fire frequency ^a	Fire density ^b				
			Mean of probability of fire given:		SD	Mean of probability of fire given:		SD						
			No fire	At least one fire		No fire	One fire				At least Two fires			
Inner	SA4	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	SA3	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	SA3	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	SA3	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	SA3	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	SA3	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	SA3	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	SA3	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	SA4	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	SA3	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	SA3	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	SA3	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	SA4	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	SA3	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	SA3	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	SA3	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	SA3	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	SA4	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	SA3	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	SA3	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	SA3	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	SA3	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	SA4	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	SA3	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	SA3	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	SA3	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	SA4	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	SA3	13	0.007	0.000	0.024	0.000	0.007	0.000	0.000	0.024	0.000	0.000	29	2.654
Maroondah	SA3	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	SA3	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	SA3	14	0.018	0.020	0.022	0.091	0.018	0.020	0.000	0.022	0.500	0.000	59	7.157

Table 5 continued

Subregion	Level	Number of grid cells	Two-state Markov chain				Three-state Markov chain				Fire frequency ^a	Fire density ^b		
			Mean of probability of fire given:		SD	Mean of probability of fire given:		SD						
			No fire	At least one fire		No fire	One fire		At least Two fires					
South East	SA4	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	SA3	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	SA3	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	SA4	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	SA3	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	SA3	90	0.023	0.012	0.034	0.113	0.023	0.012	0.000	0.034	2.212	0.000	514	11.282
Maribymong	SA3	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	SA3	13	0.006	0.000	0.024	0.000	0.006	0.000	0.000	0.024	0.000	0.000	62	10.916

^aThrough the 10-year period^bFires per 1000 dwellings

weekly, monthly, or annual basis. It depends on the phenomenon that serves as a fire-initiating or risk-enhancing factor. For bushfire in Australia, it could be sessional or annual; whilst for earthquake it could be decadal or centennial. In this study, fire risk was modeled on a monthly basis given the frequency of fire per unit of area.

Figure 7 shows the k -step transition probability where one step represents 1 month. It depicts the change in the probability of fire occurrence in certain steps (months). Here the probabilities of a three-state Markov chain are used because the three-state Markov chain as mentioned in Sect. 3.3 provides more details of the cases related to the number of past fire occurrence as starting point rather than the two-states Markov chain. The probabilities are calculated by using historical fires that occurred in 2982 grid cells. In the case of at least two fires within the neighborhood, the probability of the next fire tends to decrease after a 2-month time lag (month 2 and beyond in Fig. 7) and then becomes steady afterwards (solid line). Given one fire in the past, the probability of a fire also slightly decreases in the next 2 months and then stabilizes to a steady state. Thus, the time threshold of reduced fire risk is about 2 months (dashed line) after the occurrence of at least one fire in an area. If there has been no fire within the neighborhood in the past month, the likelihood of a fire is relatively constant and uniform across the metropolis (dotted 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 2 months in comparison to the state of one fire or no fire.

4.6 The Effect of Past Fire Over Geographic Space

The probabilities of a fire based on past fire incidents are calculated across all four designated zones (that is, within the focal cell, first-order neighbors (8-adjacent cells), second-order neighbors (16-adjacent cells), and third-order neighbors (24-adjacent cells)). Figure 8 shows the mean of the probability of fire occurrence given a number of fires occurred within the designated zones at the last month period.

Figure 8 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 (solid line) until the third-order neighbors. Given one fire within the first-order of neighbors, the probability of fire occurrence is relatively low and remains constant until the second-order neighbors, when occurrence probability drastically increases (dashed line). Similarly, given the case of no fire within the first

and second order neighbors, the probability of fire occurrence is relatively constant, but occurrence risk increases drastically when there was no fire incident up to the third-order neighbors and beyond (dot line). The second-order neighbors, which are confined within 5 km from the focal cell, represent a threshold distance where the number of fires that 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 more than two fires occurred in the past. To confront and control this fire risk situation, 47 fire stations are distributed across Melbourne's metropolitan area. Each fire station serves an area of about 15–20 km in radius. The distance of the fire station from the sites of recent fires is crucial to the fire brigade's strategic ability to elevate individual and community awareness of fire risk. This is particularly true in those areas 5 km or less away from the sites of recent fire incidents that have not themselves experienced recent fires. This targeted public education mission is essential to ensure a low level of probability of fire occurrence and a diminished fire risk in the future.

5 Policy Implications

The residential fire risk model generated in this study is a useful assessment tool, which can help implement fire safety interventions in areas where and when they are most needed. From a planning perspective, these maps of fire risk probabilities across Melbourne are also of practical and operational value to fire agencies as they provide evidence to help develop fire risk mitigation and prevention plans, improve response time to fire occurrence, and improve the efficient use of resources. The risk maps are useful visual and spatial plans, which could aid operational decision making and strategic emergency planning, such as the establishment of a new fire station. The outputs from the Markov chain model therefore provide empirical evidence for emergency response agencies to allocate resources in areas identified as having the greatest fire risk and to enhance the effectiveness of fire safety policies and interventions to build community resilience.

From a policy perspective, the analysis of historical fire incident data has generated new evidence that may help to address some of the policy questions that were not previously answered. Two key findings of this study related to the effect of space and time on fire risk are notable. The first finding relates to the space dimension of fire risk, which demystified the conventional wisdom currently prevailing in emergency management and practices that often emphasizes on immediate allocation of resources to areas with higher number of fire incidents (Blum 1970; Rhodes and Reinholdt 1998). In fact, fire risk increases

with distance from the location where the fire has occurred. Areas with higher number of fire incidents are at a lower risk of fire in comparison to areas that have had no fire in the past.

The second key finding highlights the criticality of the timing of intervention by emergency response agencies to mitigate fire risk. The likelihood of a fire diminishes in areas with a fire in the immediate past. Residents are more likely to retain information about a fire incident that occurred in their neighborhood and take actions to mitigate fire risk for a short period of time. After about 2 months, however, the past fire incident has no profound effect on fire risk levels. In other words, when this period of 2 months elapses, the difference in fire risk between areas with a fire or no fire in the immediate past becomes statistically insignificant. The risk levels are therefore affected and decided by the way fire incidents are confronted, evaluated, cognitively processed, remembered, assimilated, and connected with what we know already. Information retention can help understand the perception of fire risk as the result of memory effect.

Knowing this time threshold is vital for emergency planners when scheduling more geotargeted interventions to improve community awareness of fire risk, first in areas where there was no fire, and later immediately after a period of 2 months when fire risk levels elevate in areas where there was a fire. Often fire agencies tend to react to a fire incident by implementing post-fire incident awareness campaign; our findings indicate that during this initial 2-month period there tends to be a reduction in fire threat to residents. This reduction in fire risk, however, could be linked to risk prevention/mitigation programs that fire agencies often implement in the post-incident phase. Nonetheless, the need for an intervention in areas with no fire in the immediate past is higher than those areas with a fire.

6 Conclusion

In this article, the application of a Markov chain analysis extended the traditional methods of modeling 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. Mapping the probability of fire occurrence across metropolitan Melbourne shows a city-centric spatial pattern, where inner city subregions are relatively more vulnerable to fire than the outer subregions. The time threshold that affects fire risk levels within a neighborhood with at least one fire is about 2 months. After this period of reduced fire risk, the probability of a fire tends to attain a steady state. If there was no fire within a

neighborhood in the last 1 month, the probability of fire occurrence is relatively unchanged. This suggests that the timing of education or awareness campaigns and their frequency, location, and target audience are important. Furthermore, a fire that has occurred in an area has a significant effect on fire risk levels within its neighborhood. When a distance threshold of 5 km or the second-order neighborhood is attained, the probability of fire occurrence in areas with either one fire or no fire within those zones (that is, the second order neighborhood and beyond) in the last 1 month has insignificant effect on reducing fire risk levels. While when two or more fires still occurred up to or beyond the second-order neighborhood (greater than 5 km of distance), the risk of fire is likely to reduce.

There are limitations to the Markov chain approach adopted in this study. First, only one step backward (fires that occurred 1 month before the fire incident) is taken into account to predict 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 tragic event. Second, the selection of the 2.5×2.5 km grid cell is problematic in the analysis of the distance decay effect on the likelihood of fire occurrence. It often leads to the Modifiable Areal Unit Problem, which highlights the need for considering an appropriate unit of spatial scale to avoid generating contradictory results. Third, space and time dimensions were simply considered as mathematical expressions because of their measurable properties. They are considered as proxies for local learning and memory effect. However, space and time are often socially constructed and contextually defined.

Further research is therefore required to establish the ontologies of a space–time framework to link with psychological or cognitive aspects of human response and behavior. Despite these limitations, we believe that our model provides a spatially-integrated decision support tool that would help fire agencies with the development and implementation of policies to strengthen community resilience and the establishment of priority areas for policy interventions. The outcomes in this study that indicate the probability of residential fires need to be generalized with caution. 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 would be needed in order to strengthen the validity of the model. Different geographical and socioeconomic characteristics also should be taken into consideration.

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