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Community variations in hoax calls and suspicious fires: Geographic, temporal and socio-economic dimensions and trajectories

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Executive Summary

Understanding the dynamics of suspicious fires and malicious hoax calls

The present project seeks to better understand the spatial dynamics of suspicious fires and malicious hoax calls across Queensland. Currently an extensive body of empirical research considers the psychological motivations and disorders related to fire setting behaviour. Not surprisingly policy and prevention initiatives also focus on individual behaviours or predispositions. While some studies are beginning to consider the spatial and environmental characteristics where fires occur, the current project is the first to examine fire incidents over such a large geographic area (State of Queensland) and time period (13 years). In so doing it makes central the spaces in which malicious hoax calls and suspicious fires occur and how these incidents in these spaces change over time.

Research objectives

This research aims to examine and capture the spatial and temporal patterning of malicious hoax calls and suspicious fires across Queensland. It takes a longitudinal approach examining the geographical trajectories of malicious hoax calls and suspicious fires over time. This project aims to identify changing patterns of malicious hoax calls and suspicious fires over time by categorising changes into persistent, transient or emergent spatial concentrations. Further it identifies the most salient socio-economic characteristics of spatial areas that predict the occurrence and spatial patterning of malicious hoax calls and suspicious fires.

Methodology

This project employed three analytic techniques to examine the spatial dynamics of malicious hoax calls and suspicious fires over time: (1) cluster mapping; (2) geographically weighted regression, and; (3) trajectory modelling. These techniques required an integrated data file which was a major undertaking of the project. The sources necessary to conduct this study included Queensland Fire and Rescue Service incident data across 13 years and key variables drawn from the 1996, 2001, and 2006 Australian Bureau of Statistics (ABS) Censuses that were concorded to 2006 Census boundaries.

Our cluster mapping analyses employed spatial autocorrelation statistics across time to examine the correlations among spatial areas in relation to fire incidents and to identify clusters or 'hot spots' of fire incidents. The second approach utilised geographically weighted regression to analyse spatial relationships. Using the socio-economic characteristics of the spatial areas, measured in the national Census, we identified the key explanatory variables associated with fire incidents. The final approach adapted individual trajectory modelling approaches, developed to examine offending trajectories, to the spatial context using geographic areas as the unit of analysis. The trajectory analysis identified different types/groupings of geographic areas based on their rates of fire incidents. In this project we have deliberately applied a series of spatially orientated approaches here to offer, for the first time a more rigorous investigation of geographic and temporal variations and underlying social ecologies of malicious hoax calls and suspicious fires. Independently each technique has inherent limitations in its capacity to capture, visualise and help explain the socio-economic drivers of these fire incidents; however in combination offer the opportunity to overcome many of these to more fully unpack the complex dynamics of these fire incidents.

Results

Overall, the results emphasize the high degree to which both malicious hoax calls and suspicious fires are neither geographically or temporally uniform across the Queensland study region, rather there are specific locales (places) and times that consistently experience elevated incident levels. Innovative cluster mapping offered, for the first time, the capacity to capture the changing spatial nature of the fire incident patterns through classifying suburbs into one of three types (*persistent, emergent* and *divergent*) based upon local clustering patterns and their variation over the 13 year study period. Modelling the socio-economic and demographic variables identified the key explanatory variables associated with fire incidents that included: *the proportion of people aged between 15 and 24; the proportion of one parent families; the proportion of people who had moved house in the last five years; the proportion of people who were born in a non-English speaking country; and the proportion of unoccupied dwellings* for malicious hoax calls. For suspicious fires key determinants included: *the proportion of one parent families; the proportion of people who achieved a qualification above high school; mean household weekly income: the proportion of people who were born in a non-English speaking country; and the proportion of dwellings that were owned or being purchased.* Finally, results from the trajectory analysis highlighted that malicious hoax calls and suspicious fires are both generally in decline across the State, allied by the fact that no suburbs displayed long term increases.

Research and Policy implications

This project applied a suite of innovative methodologies through which geographical differences can be both cartographically and statistically captured. It identified the salient socio-economic and temporal characteristics that influence malicious hoax calls and suspicious fires and in so doing provides an enhanced evidence base to inform policy intervention. This project will assist in reducing the social and economic costs associated with such fires incident categories and will assist emergency service agencies in the design and implementation of appropriate fire prevention policies to enhance their use of finite resources.

Chapter 1: Background

Introduction

The relationship between man and fire has always been an imperfect one – “threatening and, at the same time, offering utility each day of our lives” (Corry, 2002, p. 75). Although we have engineered the control, use and manipulation of fire, it still poses safety concerns for the community. When fires are lit with a malicious intent or hoax calls are made to fire services, property damage, injuries or even death can result. The consequences of deliberately lit fires can be life threatening and they can incur dire repercussions for the affected communities. The consequences of hoax calls are also serious. At worst they divert services from actual incidents and endanger the lives of responding officers by causing them to engage in unnecessary, risky behaviour (e.g. speeding) (Yang, Gell, Dawson and Brown, 2003). At best, hoax calls disrupt emergency services’ preparation for legitimate call outs and waste valuable resources.

To date scholarship has considered the causes of suspicious fires and malicious hoax calls and possible prevention strategies. However, much of the research focuses on the offender and fails to consider the spatial-temporal context in which suspicious fires and hoax calls take place. The present project seeks to improve the current understanding of suspicious fires and malicious hoax calls by examining the patterns of these incidents to better understand their spatial dynamic across Queensland.

Figure 1 Study area (Queensland)

Aims and objectives of the current research

The aims of the present research are two-fold:

1. To examine and capture the spatial and temporal patterning and trajectories of malicious hoax calls and suspicious fires across Queensland; and,

2. To ascertain the most salient socio-economic predictors of malicious hoax calls and suspicious fires.

To achieve these aims, this project utilises individual level fire incident data that contains the location and timing of malicious hoax calls and suspicious fires across Queensland. We also incorporate Census data for all state suburbs across Queensland drawn from the Australian Bureau of Statistics (ABS) Census data.

This project addresses the following key questions:

- *To what degree are malicious hoax calls and suspicious fires spatially concentrated in Queensland?*
- *How does the spatial concentration of malicious hoax calls and suspicious fires vary over time and seasonally?*
- *To what degree can these trends be considered, persistent, transient or emergent spatial concentrations?*
- *What are the key socio-economic characteristics that explain the spatial dynamics of malicious hoax calls and suspicious fires and their variation over time?*
- *What trends of patterning can be observed over time in malicious hoax calls and suspicious fires when subjected to trajectory analysis techniques?*

Structure of the report

The remainder of the report is structured as follows: In Chapter 2 we review the previous research on malicious hoax calls and suspicious fires. This literature is drawn from a range of disciplines, including criminology. From this review we demonstrate the dearth of research that sets out to specifically explore the geographical patterning of malicious hoax calls and suspicious fires. In Chapter 3, we describe the data sets used in our study and discuss the spatial and statistical methods that are applied to the data. Results from the analysis are presented in Chapter 4 where we consider the main outcomes. We then summarise our project and highlight a number of potential avenues for further investigation in the final chapter.

Chapter 2: Literature Review

Suspicious Fires: Background

Deliberate fire setting first attracted academic attention in the 1950s, yet it is only recently that this phenomenon has become prevalent in academic research (see Appendices 1 and 2 for details on suspicious fire publications). Determining the cause of a fire incident can be difficult and imprecise. In some cases there may be insufficient evidence to confirm or deny whether a fire incident was deliberate, accidental or natural in origin (Bryant, 2008). The Australasian Fire Authorities Council therefore defines a fire as suspicious "where the circumstances indicate the possibility that the fire has been deliberately set" (Bryant, 2008, p.4). The literature on suspicious fires can be grouped into three focal areas: the psychology of fire setters, the geographical mapping of fire incident location and the crime prevention strategies that may reduce fire setting behaviours. Early research into suspicious fires was psychological in nature, with geographical explanations of the phenomena gaining momentum only recently. Studies considering geographical explanations of fire setting are largely concentrated in the US and to a lesser degree the UK, Australia and Canada. Although Australia has a long history of devastating bushfires, 50 percent of which are considered suspicious or deliberately lit (Muller, 2009), research into suspicious fires did not fully develop in Australia until the early 2000s.

Despite increased interest in the spatial distribution of suspicious fires, research aimed at understanding the spatial clustering of suspicious fires remains under-developed when compared to the psychological scholarship on fire setters. However, the latter approach does provide some insight into the patterns and behaviours of fire setters that help illustrate the importance of particular types of places as suitable targets and has no doubt led to an interest in the types of places where such incidents occur. Recently studies in geography have considered the socio-spatial and temporal aspects of fire incidents. In the crime prevention/policy literature, there is a strong focus on intervention programs, legalistic definitions of fire setting or arson and policies associated with fire investigation and the operation of fire services more broadly. In what follows we review the central findings of this work in more detail to elucidate what is currently known about the broader context in which fire incidents occur.

Suspicious Fires and Arson: Introduction to the empirical research

Research suggests approximately 50 percent of fires in Australia are deliberately lit (Muller, 2009). Scholarship on suspicious fires and arson can be grouped into three broad categories: fire setting as an individual phenomenon; the spatial dynamics of fire setting; and the prevention of arson/ fire setting. Much of the empirical research on this topic considers individual characteristics of fire setters and explanations for fire setting with a focus on psychopathological or motive based explanations of the behaviour. The motivations associated with fire setting include: excitement or relief from boredom; gaining recognition or attention; and obtaining a specific outcome, much like in a protest. There are also suspicious fires that are lit without a malicious motive. Developmental psychological perspectives suggest that humans are all born with an innate interest in fire - fire intrigues the senses of young children who then look towards adult role models to understand the implications of fire and how to use fire in a safe way (Pinsonneault, 2002). For the great majority of people, therefore, playing with fire does not suggest pathology but rather indicates a curious mind at work (Pinsonneault, 2002, p. 27). However, for a small group of people, fire setting may be a symptom of an underlying psychological or psychiatric disorder (Willis, 2005, p. 97). This view is supported by psychological studies in the area of fire setting and arson (for example see Del Bove et al., 2008; Gannon & Pina, 2010; Gaynor, 1996; Horley & Bowlby, 2011; Kolko, Kazdin & Meyer, 1985).

The second category of research reviewed in this report considers the contextual aspects of fires generally, as opposed to suspicious fires specifically. Development in this field of research is ongoing. To date studies concerned with the spatial aspects of fire setting tend to focus on identifying the types of places where fires occur; the temporal patterns of fire setting; and/or the structural features of the environment that may exacerbate or moderate fires once lit. Similar to other types of criminal offending, incidents of deliberate fire setting tend to cluster spatially and temporally (Genton, Butry, Gumpertz, & Prestemon, 2006).

The final category of research considered in our review examines the scholarly articles and research reports relating to specific policy initiatives and interventions aimed at the prevention of suspicious fires. We find that the majority of policies and initiatives are concerned with identifying risky individuals and reducing their propensity to engage in deliberate fire setting. For example, at the end of 2011 the National Work Plan to Reduce Deliberate Bushfires, originally endorsed in 2009, incorporated a National arson notification capability which uses a national database of criminal records to identify persons convicted and charged with arson-related offences to enable prevention and education programs to be targeted at these individuals (Australian Government, 2012). From our review we find that intervention programs are also largely targeted at individuals, in particular juvenile and recidivist arsonists. Moreover they centre on education and psychological therapies geared towards individual behavioural change (Adler et al., 1994; Melbourne Fire and Emergency Service Board, 2009) not the spatial-temporal dynamics of fire. In what follows we provide an overview of the literature comprising each of these three categories of suspicious fires and arson research.

Fire Setting as an Individual Phenomenon

Individual explanations of fire setting and arson can be divided into three main categories:

1. social learning;
2. psychopathology; and
3. socio-demographic explanations.

Social Learning Theory

Social learning theory (Vreeland & Levin, 1980 cited in Swaffer & Hollin, 1995) provides one explanation as to why young people may engage in deliberate fire setting. This perspective suggests that fire setting behaviour is learned through interactions with family and peers and reinforced through peer support and incidents of undetected fire setting (Doley, 2004). Note that while arson is defined as *fire lighting* behaviour with the intent to produce damage, *fire setting* is defined as having no ill intent (Franklin, Pucci, Arbabi, Brandt, Wahl & Taheri, 2002). Proponents of social learning theory argue that young people engage in fire setting "because youngsters learn the behaviour; that is they may observe it, imitate it, model it and perhaps even be rewarded for it" (Gaynor, 1996, p.598). However, while studies have found an association between poor family dynamics, harsh discipline, inadequate parental supervision and delinquency, including deliberate fire setting, to date there is limited empirical support for the application of social learning theory as an explanation of arson (Doley, 2004). Fire setting is a serious and costly form of antisocial behaviour and is one of few crimes that is committed more commonly by juveniles than adults (AIC, 2005). As such much of the research investigating the etiology of fire setting is concerned with children and adolescents. Studies indicate that fire setting is strongly correlated with school difficulties, other antisocial traits and co-occurring delinquent behaviours and psychiatric comorbidities (Kolko & Kazdin, 1988; Vaughn et al., 2010).

Psychopathology

From as early as the 1800s, arson was linked to a morbid impulse or lust towards fire play, what is now referred to as pyromania or fire mania[1]. Pyromania is considered a psychological disorder and is

[1] Presently there is continued debate on the utility of psychological impairment as an adequate explanation for arson (Andrews, 2010)

recognised as such in the Diagnostic and Statistical Manual of Mental Disorders (DSM) and International Statistical Classification of Diseases and Related Health Problems (ICD) (Bohnert, Ropohl, & Pollak, 1999). Pyromania and arson have been associated with puberty and childhood since the early 1900s. At that time, Gross (1911/1998 cited in Andrews, 2010) suggested that children were devoid of responsibilities and experiences and less cognisant of the implications of their actions. Thus they were more susceptible to blind imitation and more likely than adults to engage in fire setting. In the contemporary literature the link between age and fire setting remains with research showing that children under 18 years are responsible for approximately 80 percent of incendiary fires in large cities (Raines & Foy, 1994). Faranda and colleagues (2005) report that in 1999 juveniles accounted for 55 percent of arson arrests in the US. In terms of financial costs, in New South Wales, between 1987 and 1994, fires caused by children resulted in losses of $24 million (Muller & Stebbins, 2007).

Various explanations are offered for juvenile fire setting which include: revenge, concealment of another crime, peer pressure or psychological impairment (Swaffer & Hollin, 1995). The majority of research finds that fire setting in adolescence tends to co-occur with a range of antisocial and delinquent behaviours (Del Bove, Caprara, Pastorelli & Paciello, 2008; Martin, Bergen, Richardson, Roeger & Allison, 2004; Räsänen, Hirvenoja, Hakko & Väisänen, 1995). In 2008, Del Bove and colleagues examined individual characteristics associated with self reported antisocial or aggressive behaviour in a sample of 567 adolescents aged between 11 and 18 years. Results of the study indicate a significant association between self-reported fire setting and aggression, social withdrawal and delinquency more broadly (Del Bove, Caprara, Pastorelli & Paciello, 2008). In further analyses Del Bove and colleagues (2008) separated the fire setter and non-fire setter groups into aggressive and non-aggressive youth and found that fire setting was a stronger predictor of future delinquent behaviour than aggression. Similarly, Martin and colleagues (2004) studied 2596 Australian high school students and found that compared to non-fire setters, fire setting youth reported higher levels of antisocial behaviour, drug use and risk taking behaviour. Additionally, Kolko and colleagues (1988; 1994; 1985) reported a high prevalence of fire setting among a sample of children diagnosed with a psychiatric illness. Research suggests that girls are less likely to engage in fire setting than boys and that the predictors of antisocial behaviours, such as fire setting, differ across gender (Kosky & Silburn, 1984; MacKay, Feldberg, Ward & Marton, 2012; Räsänen, Hirvenoja, Hakko & Väisänen, 1995).

While the existing literature on deliberate fire setting focuses primarily on young people, a small number of studies examine adult fire setters (see for example Barnett, Richter, & Renneberg, 1999 and Labree, Nijman, van Marle & Rassin, 2010). Adult fire setters display many of the same characteristics as children and adolescents who engage in the behaviour. Further, as is the case with young people, arson and deliberate fire setting in adults is commonly associated with psychopathology (Labree et al., 2010). A study examining the criminal careers of arsonists in Germany found that in comparison to criminally liable arsonists, those granted diminished responsibility due to psychiatric diagnosis did not commit any crimes other than fire setting but engaged in the highest number of fire setting incidents (Barnett, Richter, & Renneberg, 1999). While some fire setting is associated with pscyhopathology, research suggests that specialist arsonists, individuals for whom arson is their prodominent form of offending, comprise a minoirity of fire setters. For the majority of individuals who engage in arson, fire setting is part of a much wider pattern of criminal and antisocial behaviour (AIC, 2009; Muller, 2008). A review of arson cases that appeared before the NSW courts between 2001 and 2006 found that while most offenders had no previous record of fire setting, over half had previous convictions for other crimes (Muller, 2008). Similarly, a study conducted in the UK reported that 65 percent of arsonists appearing before the courts between 1999-2003 had prior convictions for other crimes (Jayaraman & Frazer, 2006).

Socio-demographic charactersitics

Other research suggests that fire setting behaviours are influenced by socio-demographic characteristics at both the level of the individual and the community. For example, coming from a large family and a low socio-economic background is associated with fire setting in both adults and juveniles (Heath, Hardesty, Goldfine, & Walker, 1983). Adult arsonists are overwhemingly white, socially isolated young males (Inciardi, 1970; Labree et al., 2010) and juvenile fire setters are more likely than non-fire setters to report experiences of childhood trauma; low levels of emotional and developmental support and poor family functioning (Lyons, McClelland, & Jordan, 2010). Disadvantage, poor social skills and social isolation are also associated with an increased risk of engaging in fire setting for young people (Gannon & Pina, 2010; Horley & Bowlby, 2011; Martin, Bergen, Richardson, Roeger, & Allison, 2004). This finding is not surprising given the well established relationship between disadvantage and criminal offending more broadly (Agnew, 1999; Rutter, Giller & Hagell, 1998; Farrington, 1990; Kelly, 2000; Sampson & Laub, 2003).

The Spatial and Temporal Dimensions of Suspicious Fires/ Arson

While early studies proferred mainly individual level explanations of fire setting and arson, more recently scholars are considering the relationship between the fire setter and the incident location. Scholars are now examining the spatial aspects of fire setting including distance travelled to the site of the fire and the spatial patterning of incidents. Research shows some communities may have a higher propensity for suspicious fires than others (AIC, 2009; Prestemon & Butry, 2005). As found in the broader criminological literature, there is some evidence to suggest that communities characterised by disadvantage experience a greater number of suspicious fires (Beale & Jones, 2011; Prestemon & Butry, 2005). For example, a study conducted in Florida using data spanning an eight year period found that communities with higher levels of poverty experienced increased incidence of suspicious fires. Further, using time series analyses, Prestemon and Butry (2005) found that modest increases in average earnings was associated with a significant decrease in fire incidents in a given community.

The spatial and temporal dimensions of suspicious fires and arson are investigated using a range of techniques underpinned by Geographical Information System (GIS)-based software and interfaced with a variety of statistical methods including Regression Tree Analysis (Aldersley, Murray & Cornell, 2011; Holmes, Wang & Ziedins, 2009; Wang, Ziedins, Holmes & Challands, 2012), Bayesian approaches (Rohde, Corcoran & Chhetri, 2010) and Kernel Density Estimation (KDE) (see for example Corcoran, Higgs, Brunsdon, Ware & Norman, 2007). The spatial scale at which analyses are conducted varies across international contexts but, most commonly, they are performed at the level of the county in the UK (for example see Brown, Hirschfield, Merrall, Bowers & Marsden, 1999; Maingi & Henry, 2007; Prestemon & Butry, 2002), the Census tract in the USA (see Jennings, 1999; Wallace & Wallace, 1984) or the collection district in Australia (see Corcoran, Higgs & Higginson, 2011). To date studies concerned with spatial aspects of fire setting focus on: identifying the types of places where fires occur; the temporal patterns of fire setting; and/or the structural features of the environment that may exacerbate or moderate the spread of fires once lit.

Studies mapping intentionally lit fires in the US, UK, Australia and New Zealand indicate that fire setting, not unlike other types of criminal activity, is spatially clustered in particular types of places (Brown, Hirschfield, Merrall, Bowers, & Marsden, 1999). For example, Brown and colleagues (1999) examined incidents of residential and vehicle arson across Manchester and found both to be highly concentrated in particular areas of the county. Further, research reveals that arson “hotspots”, or clusters of fire incidents, tend to be characterised by social and economic disadvantage (Corcoran, Higgs, Brunsdon, Ware, & Norman, 2007; Corcoran, Higgs, & Higginson, 2011; Duncanson, Woodward, & Reid, 2002; Johnson Gaither et al., 2011). In addition to disadvantage, close proximity to urban settlements and low quality road access – affording access to the site but carrying little other traffic – characterise places where suspicious fires tend to cluster (Willis, 2004). Looking specifically at bushfire arson in the Beerburrum fire district, Christenson (2007) attributed high bushfire density (or the “hotspot” of fire setting) in this locale to the encroaching populations from Brisbane and the Gold Coast. He found that area characteristics, including proximity to population centres and low levels of forestry staff, were associated with high rates of arson in this district.

Other studies have incorporated a temporal dimension to identify where and when arson is most likely to occur (Asgary, Ghaffari, & Levy, 2010). Across a 24 hour period in Canada, suspicious fires were most likely to occur between midnight and noon with the highest number of incidents recorded between midnight and 3am (Aspary, Ghaffari & Levy, 2010). Further, incidents of fire setting clustered temporally on non-school days, including weekends and school holidays, and spatially in neighbourhoods characterised by disadvantage (Aspary, Ghaffari & Levy, 2010). Similarly, in Australia, the pattern of deliberately lit fires is consistent with everyday patterns of movement and activity that impact guardianship and opportunities for fire setting. Deliberate fires are most likely to occur between 6pm and 6am, on weekends and are most evident in socially disadvantaged urban and semi-urban areas (Bryant, 2008). This pattern is consistent with the common temporal frame for criminal offences more broadly which, research shows, increase at times when individuals have less habitual routine activities including after dark, on weekends and during holiday periods (Cohn, 1996).

Temporal studies also highlight the complex nature of both fire ignition and spread and the many factors which must be considered when examining the issue of deliberate fire setting. A small number of studies are beginning to consider the longitudinal patterns of fire setting and the contextual factors that influence the spatial distribution of fire setting over time. For example, Genton and colleagues (2006) examined the incidence of wildfire arson in Florida between 1981 and 2001. They found that arson was clustered both spatially and temporally. Observations indicated that years recording high rates of arson were followed by periods of low rates of arson. Investigating incidents of deliberate fire setting across a 20 year period, Vazquez and Moreno (2001) found particular structural elements of the environment, including vegetation type, landscape features and climatic conditions, were associated with arson incidence. While some elements, such as seasonal changes, cannot be controlled, specific characteristics of the environment can be adapted to reduce the risk of fires spreading in the event of a suspicious fire. High density infrastructure such as roads, rail lines and populated properties and frequent back burning were associated with lower incidence and reduced intensity of fires (Malingi & Hentry, 2007).

Suspicious Fires/ Arson Prevention

We now turn our attention to the arson prevention literature. Suspicious fires have significant social and economic implications for both individuals and communities. Much of the existing research on the prevention of suspicious fires considers the psychological dimensions of fire setting and focuses on interventions for distinct typologies of fire setters. Evaluations of these interventions suggest multi-agency and third party intervention programs that (i) educate retailers and parents of the dangers of ignition materials; (ii) distribute educational pamphlets about fire to adults and children; and (iii) provide integrated prevention plans for repeat fire setters (incorporating mental health services, schools, police and fire and rescue services) are most effective for arson prevention (Henderson & MacKay, 2009; Muller & Stebbins, 2007).

Arson prevention strategies have recently broadened to consider the geographical and environmental factors associated with fire setting, though here the focus is specifically on bushfires (see Muller, 2009). In the Australian context, deliberately lit bushfires receive the greatest attention from governments and agencies as a result of the widespread damage they cause. In 2009 the Australian Government, State and Territory police and emergency services ministers endorsed the National Work Plan to Reduce Deliberate Bushfires, a nationally agreed upon policy framework to address bushfire arson in Australia. Since the endorsement of the 10 step work plan Australia's national bushfire arson policy has progressed significantly. The National Strategy for the Prevention of Bushfire Arson was sanctioned by all states and territories in 2011. The strategy is based on four principles:

1- national consistency of action in relation to preventing bushfire arson;

2- information sharing between jurisdictions;

3- collaboration between agencies and across borders to disrupt bushfire arson activities and detect patterns indicating bushfire arson activity; and

4- consistency and interoperability to improve the effectiveness of bushfire arson reduction initiatives.

Further development of this strategy in 2011 secured the launch of a national bushfire arson notification capability to assist in the identification of high risk individuals. The capability uses the National Police Reference System, an existing database of criminal records, to alert police of possible arsonists in a particular area and make it easier to identify individuals convicted of, charged with or suspected of bushfire arson and related offences. Other prevention activities that fall under the National Strategy for the Prevention of Bushfire Arson include: fuel reduction and prescribed burning; controlling access and reinforcing guardianship of national parks and rural properties; removing abandoned cars; bushfire arson education; identifying bushfire arson "hot spots" and targeting bushfire prone communities and; juvenile intervention programs (Australian Government, 2012).

The limited research that considers fire setting prevention from an ecological perspective emphasises reducing physical opportunities for suspicious fires and arson through environmental adaptation (Muller, 2009). However, existing research in this area is comprised almost exclusively of case studies limiting the capacity to generalise findings. Further, numerous studies elucidate spatial variation in the effectiveness of prevention strategies aimed at fire setting specifically (Andrews, 2011; Prestemon & Butry, 2005), and crime more broadly suggesting that place characteristics, such as disadvantage, may influence the success of prevention strategies (Prestemon & Butry, 2005). However, as so little information exists that considers the contexts that influence suspicious fires over time, there is little evidence base for policy and practice to drive ecologically based prevention initiatives.

Malicious Hoax Calls Literature

In this project we are concerned not only with developing a stronger understanding of the spatial patterning of suspicious fires, but are also interested in investigating the spatial dynamics of malicious hoax calls, which also pose a threat to emergency services and public safety. Malicious hoax calls are calls to emergency services requesting attendance to an incident that does not exist. In Australia, hoax calls comprise a small but notable proportion of total calls for service. Research indicates that in South East Queensland two per cent of all emergency service callouts are hoax calls (Corcoran, Higgs & Higginson, 2011). While this is a low proportion of the overall calls for service, the cost of these malicious hoax calls is very high. Malicious hoax calls therefore pose a serious problem for emergency service responders. Though exact costs are not yet available in Australia, in the UK malicious hoax calls to the fire brigade cost taxpayers more than £42 million (approximately AUD$64 million) in a single calendar year (Nugent & Sidders, 2008).

Studies specifically addressing hoax calls, as a phenomena separate from suspicious fires, are very limited in number (see Appendices 1 and 2). The majority of articles on the topic of hoax calls are policy documents, predominantly emanating from the US and to a lesser degree, the UK. Existing studies consider hoax calls to emergency services in general rather than focusing on those to fire services specifically. For example, Garcia and Parmer (1999) employed conversation analysis to examine how emergency call handlers interpret cues to differentiate genuine calls from hoax calls. Two exceptions are studies by Yang and colleagues (2003) and Cadwallader (2009) examining the spatial and temporal distribution, respectively, of hoax calls made to fire services. Yang and colleagues' (2003) mapping of the geographic locations of hoax calls to fire services in the UK revealed that calls did cluster spatially. Further, examining fire calls from an industrial complex over a 12 year period Cadwallader (2009) found fire alarms, both genuine and false, made by person or a detection system, varied systematically by temporal elements (Cadwallader, 2009). The limited number of research articles on malicious hoax calls highlights how little is known about the phenomena.

Policy Initiatives and Interventions to Address Malicious Hoax Calls

In Australia, making vexatious calls to emergency services is a serious offence under the *Criminal Code Act 1995*. In 2008, in an effort to reduce nuisance calls to emergency services the Queensland State Government launched an education campaign and amended the Fire and Rescue Service legislation to increase the penalty for making hoax calls to up to $10,000 or one year imprisonment. Further policy changes in Australia in 2008 amended the *Telecommunications (Emergency Call Service) Determination 2002* to require the Australian Communications and Media Authority to introduce a short recorded voice announcement for the Triple Zero service. The aim of the recorded voice announcement was to reduce the high level of non-genuine calls received by emergency services and reduce the strain on finite resources.

The majority of policy documents addressing the issue of hoax calls refer to the financial burden of false and unwanted calls to emergency services and state explicitly that the primary goal of initiatives is to reduce economic losses (Blackstone, Buck, & Hakim, 2005; Blackstone, Buck, & Hakim, 2007). Documents highlight the difficult task faced by dispatch operators responsible for allocating emergency service personnel. Call centre staff are often faced with uncertainty and lack of information and thus cannot always accurately differentiate between genuine and false calls (Forslund, Kihlgren, & Kihlgren, 2004). A limited number of studies indicate that the majority of malicious hoax calls originate from payphones and mobile phones. Mobile phone usage has increased exponentially in the last decade across all age, cultural and social groups (Goggin, 2006). The availability of mobile phones, in particular pre-paid mobiles that are not registered to a residential address, has made tracking hoax calls increasingly complex. In contrast to the steady rise in mobile phone usage, the number of payphones in major cities has decreased significantly in the last ten years (The Australian Communications and Media Authority, 2010). In rural and disadvantaged areas, where mobile service is unreliable or individuals are unable to afford ongoing mobile service, the decline in payphone availability has been less dramatic. Thus, access to payphones and mobile phones differs across place and social class, suggesting geographic variations in opportunities for hoax calls. The relationship between contextual characteristics, opportunities for hoax calls and actual incidence of hoax calls to emergency services is yet to be considered in the current literature. We note that this is an area for future research.

There is little evaluative research on strategies to prevent and/or address malicious hoax calls. Sampson (2004) suggested identifying hot spot pay phones (public phones registering a high volume of hoax calls) and applying situational crime prevention strategies to reduce their incidence. She outlined several initiatives, based on the principles of situational crime prevention and hot spots identification, that may reduce hoax calls such as: installing signs noting the penalty for making hoax calls at hot spot pay phones, relocating or removing public phones registering high numbers of hoax calls or targeting education campaigns at schools in close proximity to pay phones registering a high number of hoax calls (Sampson, 2004). While this limited scholarship offers potential responses to the issue of malicious hoax calls these are yet to be empirically tested and new communications technology continues to pose additional challenges (Sampson, 2004).

The Present Research

Geographical studies of crime are growing in importance in criminology, with an increasing recognition that this approach can yield important insights (see Weisburd, 2005). Scholars suggest that an analysis of geographical places offers the potential to better assess opportunities for offending and enhance the overall understanding of the crime equation (see for example Green, 1996; McCord & Ratcliffe, 2007; Nelson, Bromley & Thomas, 2001; Weisburd, Bushway, Lum & Yang, 2004). Research in this area has also lead to the development of techniques to identify crime clusters that have facilitated crime prevention strategies such as hotspot patrols or other high visibility policing initiatives (Ratcliffe, 2004; Sherman & Weisburd, 1995). Moreover such prevention techniques have been shown to be highly efficacious with substantial reductions in crime related activities recorded at sites where such strategies have been implemented (see for example Braga, 2001; Skogan & Frydl, 2003).

The extant literature on suspicious fires (or arson) and malicious hoax calls indicates that these incidents cluster both spatially and at particular times of the year (see for example, Corcoran et al., 2007). However, at the time of writing, there has been no attempt to model the occurrence of these incidents across both time and space. Thus while we know that certain places are likely 'hotspots' of activity, we can say little about the geographic stability of these places over time. Understanding the temporal dynamics of these spatial concentrations is critical in allowing for the development of more evidence based crime prevention measures and the deployment of finite emergency response resources. For example, by knowing that a particular spatial concentration of crime was highly changeable over time, the allocation of resources can be appropriately deployed when the temporal dimension is considered.

Suspicious fires and malicious hoax calls are a major concern in Australia. This report advances the idea that many of these incidents may be prevented if we understand where they are likely to occur and the conditions that influence their trajectories across time. Through the application of advanced geographic and temporal modelling techniques to identify the determinants of malicious hoax calls and suspicious fires, our research extends the literature in three main ways:

1- it highlights the place characteristics associated with a higher propensity for suspicious fires and malicious hoax calls across Queensland;
2- it identifies and models the spatial dynamics of suspicious fires and malicious hoax calls;
3- it examines and models the stability of incident prevalence across time

Drawing on individual level fire incident data describing the location and timing of malicious hoax calls and suspicious fires and ABS Census data over a 13 year period, we address the research questions posted in Chapter 1 in subsequent chapters.

Chapter 3: Methodology

The focus of this research is on the dynamics that provide opportunities for criminal acts as they relate to malicious hoax calls and suspicious fires. The methodology comprises 5 main components: the development of the methodological framework; database integration, descriptive mapping, and analysis; cluster mapping; spatial modelling; and trajectory analysis. These are described below in more detail.

(1) Methodological framework development

Component 1 is concerned with establishing the methodological framework through which the analysis techniques will be applied to identify the different types of clusters of offences and the changing nature of these clusters over time. While in this research these techniques will be developed for the examination of suspicious fires and malicious hoax calls, with other data sources the methods can have a broader application. The goal of the present research is to apply a methodology that allows for the description of the extent, shape, and evolution of clusters over time.

<u>Different types of clusters</u>: Four main types of clusters are identified (following the work on local indicators of spatial association by Anselin, 1995) with each being statistically characterised by a particular geographic concentration of incidents. First there are areas that are characterised by high levels of fire incidence and are also neighboured by areas that are characterised by high levels of fire incidence (high-high). Existing research has commonly referred to these areas as 'hotspots' (Ratcliffe, 2004). Also of importance to the current research are 'coldspots'. These are areas that are characterised by low levels of fire incidence and surrounded by other areas with low levels of fire incidence (low-low). The final types of area are those that are high in fire incidence surrounded by areas that are low (high-low) and vice-versa (low-high); these are considered outliers.

The current project also includes an examination of the changing nature of the clusters over time. Cluster types are identified annually over the 13 years of available data. They are compared on the basis of their stability and change over time. The temporal character of the clusters is broadly divided into three main typologies: *persistent, emergent*, and *transient*. *Persistent clusters* are considered those that maintain their type over time. *Emergent clusters* are those that commence as one type of cluster then over time evolve and remain as a different type of cluster. *Transient clusters* are those that regularly change cluster type back and forth between cluster types.

Another way to examine the incidence of malicious hoax calls and suspicious fires over time is to use trajectory analysis (Nagin, 1999) and then after identifying the trajectories, map the different types of trajectories (Weisburd et al, 2004). Group based trajectory analysis was originally developed for investigating similar developmental clusters when examining change in individuals' offending over time. For Weisburd and his colleagues (2004), this technique allowed for the identification and mapping of trajectories that evidenced increasing, decreasing and stable crime rates over time. Collectively, these different methodological approaches allow the examination of an important gap in the current knowledge of crime at micro places; more specifically the stability of crime in these areas over time.

Finally, identifying the temporal and socio-economic factors that are related to these types of changes in both the nature and size of these offence clusters will elucidate opportunities for crime prevention and requirements for resource deployment.

(2) Database integration, descriptive mapping and analysis

Component 2 is concerned with establishing the necessary integrated databases to support the methodological framework. The following details each of these formerly disparate databases in turn highlighting the variables that are captured in each case.

Data sources: The Queensland Fire and Rescue Service database

This database provided 13 years of fire incident data (covering the time frame 1/1/1998 to 31/12/2010) describing the location and timing of every call-out to a malicious hoax call and suspicious fire across Queensland. We geocoded all incidents in this database to enable the study of their spatial variation across time.

Date	Time	Location (x,y)	Incident type	Complex
1/1/1998	00:01	54000, 34000	Malicious Hoax Call	Public recreation complex
1/1/1998	22:10	54000, 34000	Suspicious Fires	Education facility
⋮	⋮	⋮	⋮	⋮
31/12/2010	09:34	54000, 34000	Suspicious Fires	National Park
31/12/2010	13:22	54000, 34000	Malicious Hoax Call	Dwelling
31/12/2010	15:57	54000, 34000	Malicious Hoax Call	Property without current use

Table 1: Fire incident database

Data sources: Census

Census data were retrieved through consultation with the Australian Bureau of Statistics (ABS) drawing variables from the 1996, 2001, and 2006 Censuses for State Suburbs (SSs) to temporally align with the fire incident database. The Census data sets (specifically the 1996 and 2001 Censuses) were concorded to the 2006 SS boundary system employing the ABS concordance files[2] resulting in a single geography, i.e. the 2006 SS geography that is common across the 3 Censuses. Variable selection was informed by previous research by PI Corcoran using Brisbane and Cardiff (UK) fire data (Corcoran et al., 2010) in addition to previous ecological research on socio-economic drivers of fire incidence (Jennings, 1999; Chandler et al., 1984; Gunther, 1981). The full list of Census variables extracted for Census SSs are given in Table 2.

Composite variable	**Census variable** (proportion of resident population)
Income	Household income Median household income
Family	Couple family, no children Single parent w/ children under 15 Single parent w/ dependent students (15-24) Couple family w/ children under 15 Couple family w/ dependent students (15-24)
Cars	No vehicles in household 1 vehicle in household 2 vehicles in household 3 or more vehicles in household
Qualifications	No formal qualifications Year 10 or equivalent Year 12 or equivalent Certificate or advanced diploma level Degree or postgraduate level
Tenure	Owned outright Purchasing (incl. Rent-to-buy & shared) Rent from council/state housing scheme Non-govt renting (includes private & social) Other tenure type
Accommodation	Unoccupied premises Detached house Semidetached (incl. townhouse, terrace) Flat, unit or apartment Other (incl. vans, mobile or temporary) In or attached to commercial building
Ethnicity	Born in Australia Born in New Zealand Born in NW or SE Europe Born in North Africa or Mediterranean Born in NE, SE or Southern & Central Asia Born in the Americas Born in Sub-Saharan Africa

Table 2: Census variables database

[2] Given that SS boundaries between the 1996, 2001 and 2006 Censuses differ markedly as a result of changes in the underlying population, a correspondence (also known as concordance) adjustment is required. The geography section of the ABS used their approved area based computation to adjust values for all extracted variables placing the 1996 and 2001 Censuses on the 2006 SS boundary system.

Finally, a combination of standard and custom functions in database (Microsoft Access) and GIS software (ArcGIS) are used to integrate these formerly disparate data sets, namely fire incidents and Census variables into a single data set. The data were combined in such a way that individual fire incident information was coupled with the socio-economic variables describing the area in which the emergency incident occurred (taken from either the 1996, 2001 or 2006 Censuses according to which is nearest in time) to generate a single record.

Once in this format, descriptive mapping and analysis is applied to explore the geographic patterning and seasonal characteristics of the combined data. This follows a similar method to that described in Corcoran et al., (2007) in which rate maps were generated using administrative boundaries such as SSs. Hotspot analyses are conducted using kernel density analysis (see Ratcliffe & McCullagh, 1999 and Weisburd, 2004, for examples of this type of analysis using crime data). In addition, statistical analyses are conducted to explore the seasonal component and the degree to which malicious hoax calls and suspicious fires display seasonality.

(3) Cluster mapping

The cluster mapping component of the project employs two key statistical measures to assess the degree of dependency among observations in spatially adjacent SSs. These measures are more generically termed spatial autocorrelation statistics in the spatial science literature, of which there are two main types; *global* and *local*. The global version measures the degree to which fire incidents across SSs exhibit either, positive spatial autocorrelation (i.e. areas of high counts/rates of fires surrounded by SSs having similarly high rate/counts) or, negative spatial autocorrelation (i.e. where SSs possess low and high rates of fire occur adjacent to one another) across the entire study region. The Moran's I statistic (Moran, 1950) is used to determine the existence of spatial autocorrelation at the global scale (i.e. Queensland).

In addition to the global measure the local variant of the Moran's I statistic is employed to determine evidence of local spatial autocorrelation, recognising there is the possibility of spatial heterogeneity and that the degree of autocorrelation may vary across our study region (Queensland). The importance of locally varying spatial patterns and in particular the identification of hotspot areas has been identified by Getis and Ord (1992) and more recently in relation to crime by Ratcliffe (2010). Ratcliffe (2010) also articulates that the local Moran's I statistical approach can help to identify sub-regions of greater spatial homogeneity and as a result may be less vulnerable to the modifiable areal unit problem (MAUP) (Openshaw, 1984; 1977) where the outcome of this analysis has the potential to change if different zonal boundaries are used (for example different Census geographies such as statistical local areas or local government areas), or alternatively if different scales of aggregation are employed (Openshaw, 1984, p.32).

There are two key outputs from the local Moran's I analysis, the Moran scatter plot and the cluster map; these are used in conjunction with one another (see Figure 2 for an example). The Moran scatter plot is used to visualise how the local Moran statistic contributes to the overall the global Moran. The horizontal axis shows the normalised value of the attribute of each area while the vertical axis shows the normalised spatially weighted value of the neighbouring areas. Each point in the scatter plot shows the extent of the local spatial autocorrelation while the fitted regression line shows the extent of global spatial correlation. There are four important areas to the scatter plot formed by the vertical and horizontal axes that describe an area to be either a spatial cluster or outlier. A spatial cluster can either be high values of a variable (such as malicious hoax calls) surrounded by similarly high values or the opposed scenario, low values surrounded by low values. A spatial outlier on the other hand is indicative of areas that have high values, surrounded by areas that have low values or vice versa. Using the second output (the cluster map in Figure 2) the spatial distribution of both the cluster and outliers can be visualised.

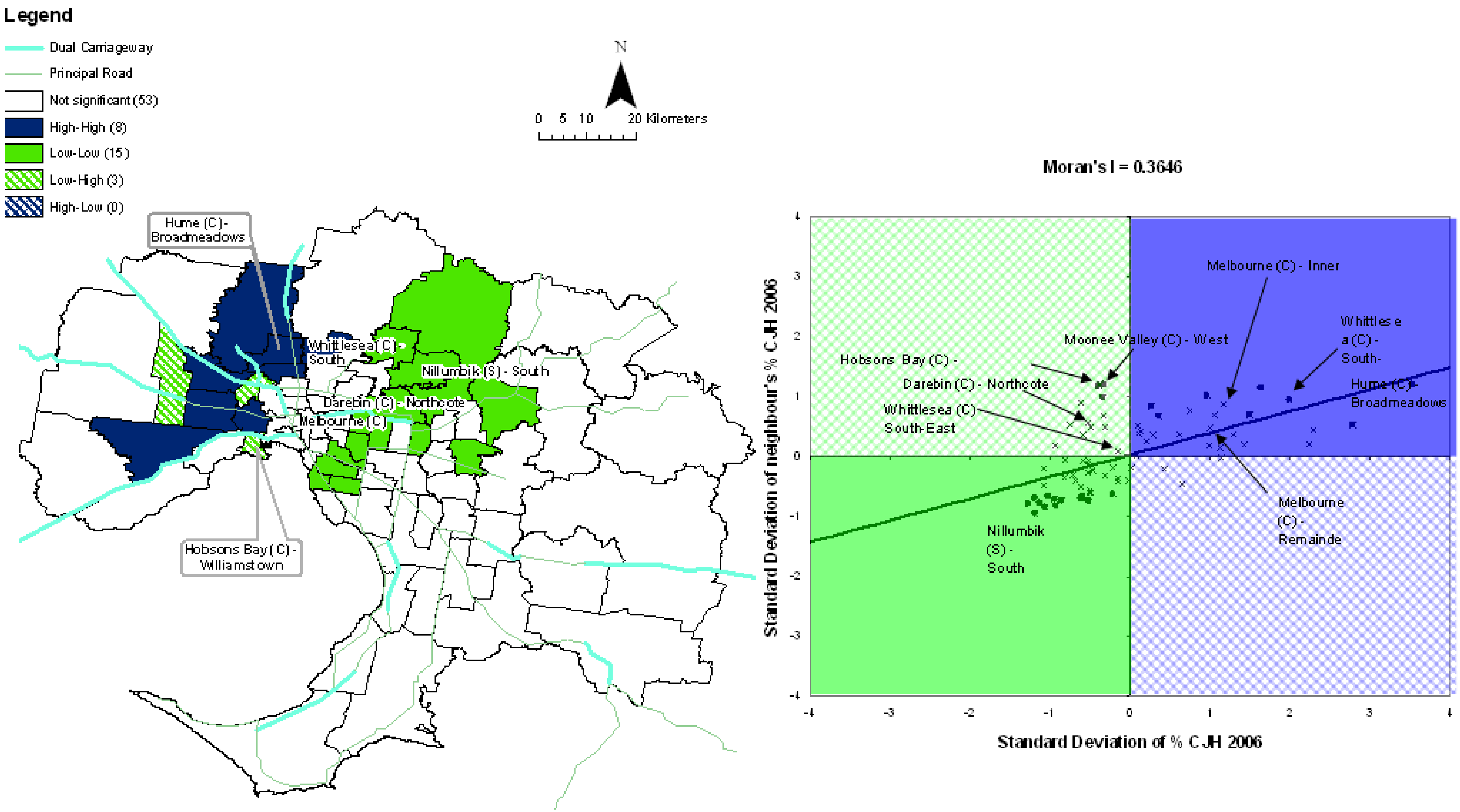


Figure 2: Moran cluster map and scatter plot (Source: Vidyattama et al., 2010)

To use the local Moran technique to identify changes in the spatial clustering over time, an augmentation of the original technique is used to track the evolution of spatial clusters and outliers over time (see Figure 3). To create the plot in Figure 3 the 13 years of fire data are used and the local Moran statistic is computed for each year (1998 to 2010). The result of this computation is then graphed for each SS in a single Moran scatter plot, which has been termed a *Moran temporal plot* (Figure 3). Each year, for which the local Moran's I is computed, is represented as either a square (statistically significant) or a circle (not statistically significant) to depict whether or not the local Moran's I score for that particular year was statistically significant. All years are plotted within a single graphic using the square and circle representation, as in the example Moran temporal plot displayed in Figure 3. The *Moran temporal plot* is a simplified summary of temporal movement and appears at the base of Figure 3. This simplified summary depicts the change in cluster or outlier type (and associated statistical significance) over the 13 year period using the same square and circle symbology as previously described. By adopting this innovative technique and coupling each of the components of this figure together, the scatterplot and the summary of change permits a qualitative visual assessment of whether a SS might be considered, *persistent*, *transient* or *emergent*.

A simple heuristic was defined to help distinguish between the 3 types (*persistent*, *transient* or *emergent*) based on the number and type of statistically significant transitions; a transition refers to the change in cluster/outlier type in adjacent years. Using the simplified summary of temporal movement at the base of Figure 3, statistically significant transitions (i.e. two adjacent years that both are represented using a square indicative of a statistically significant result) can be summed and described in terms of the number of years in which a particular SS exhibited one of the four types of cluster/outlier (i.e. high-high, low-low, high-low and low-high).

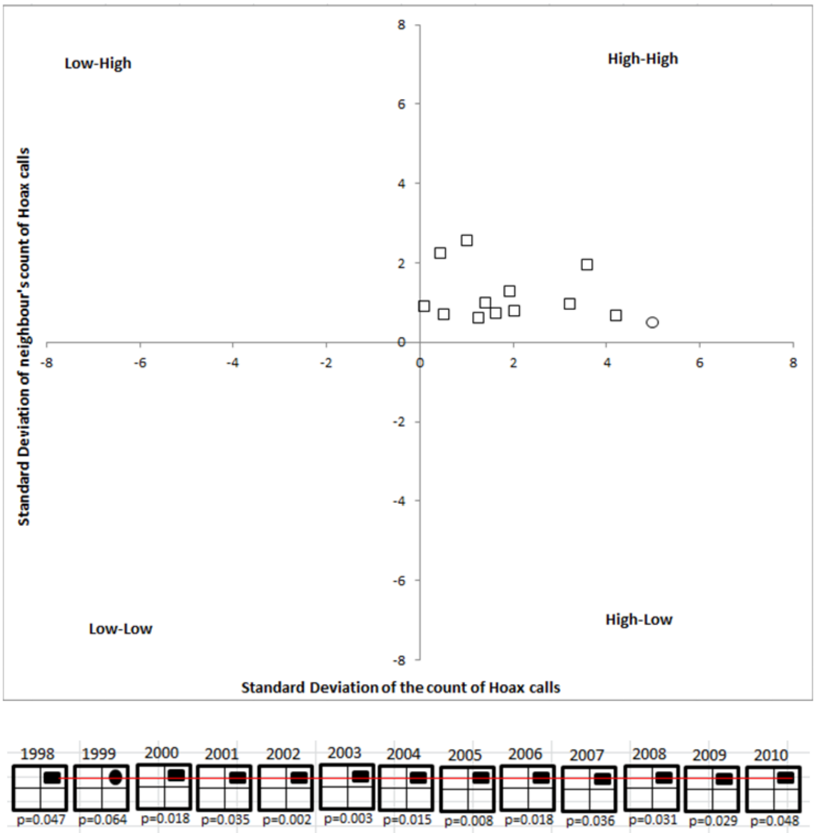


Figure 3: An example Moran temporal plot

A *persistent* locale was defined as an SS where =>50% of significant transitions[3] were in one cluster/outlier type. An *emergent* locale had at least 25% of significant transitions in one cluster/outlier type and 25% in another. *Emergent* locales were defined as areas that experienced >50% of significant transitions varied between various cluster and outlier types. Finally, areas that experienced =>75% of transitions as not statistically significant were grouped in a final category, termed *none*. Given that this is the first research of its kind, there are no previous studies that develop a standard in regards to establishing these values. As such, we have developed these bounds heuristically through exhaustively plotting all suburbs across the State and then adjusting the bounds to inspect the impact on how the locale is classified, (i.e. into one of the three categories; *persistent*, *emergent* or *transient*). Following this exercise, the bounds suggested previously offered the most representative classification of the patterns present with both the suspicious fires and malicious hoax call datasets.

[3] A significant transition refers to two adjacent years in which a statistically significant local Moran's I score exists for the same SS. In other words suburb *X* being part of a significant high-high cluster in 1998 and again in 1999 would be considered a 'significant transition'.

(4) Spatial modelling

The spatial modelling component of the methodology identifies the drivers of malicious hoax call and suspicious fire incidents through modelling the relationships using geographically weighted regression (GWR) (Fotheringham, et al., 2002). GWR is a local multivariate regression technique that weights data samples based on their spatial proximity, accounting for local variations in ecological relationships. It differs from the more traditional global Ordinary Least Squares (OLS) regression approach that is unable to capture this phenomenon. It produces a separate set of regression parameters for every observation across the study area. Therefore, it relaxes the assumption in the traditional OLS models that the relationships (regression coefficients) between the dependant and the independent variables being modelled are constant across a study area, as seen in Equation 5:

$$y = ß_0 + ß_1x_1 + \varepsilon \qquad (1)$$

where: y is the dependent variable; x_1 is the independent variable; $ß_0$ and $ß_1$ are the parameters to be estimated and ε is a random error term, assumed to be normally distributed.

In this instance, $ß_0$ and $ß_1$ are assumed to be constant across the region in a classical ordinary least squares regression. Where there is any geographical variation in the relationships between y and both $ß_0$ and $ß_1$, it will be captured in the error term.

When using the Ordinary Least Squares (OLS), the parameters can be estimated by solving:

$$ß = (X^TX)^{-1}X^TY \qquad (2)$$

Comparatively, the specific GWR model for each observation point g is specified as:

$$y(i) = ß_0(i) + ß_1(i)x_1 + \varepsilon \qquad (3)$$

where i represents the vector of co-ordinates of the location, which indicates that there is a separate set of parameters for each of the g observations.

When using GWR, the parameters can be estimated by solving:

$$ß(i)=(X^TW(i)X)^{-1}X^TW(i)Y \qquad (4)$$

where $W(g)$ is the weight matrix denoting the connectivity between the observations.

The weight can be determined by several methods. Two common methods are the bi-square function and the Gaussian function. In the instance of the Gaussian function, the weight for the observation i is shown in Equation 5:

W(i)=exp(-d/h)2 (5)

where d is the Euclidean distance between the location of observation i and location g and h is a quantity known as the bandwidth of the sampled observations. The bandwidth may be defined either by a given distance or a fixed number of nearest neighbours from the analysis location. The optimal number of the nearest neighbours is determined by minimising the Cross Validation score (CV) or through selecting the model with the lowest Akaike Information Criterion (AIC) score (Hurvich et al., 1989), given as:

$$AIC_c = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left\{\frac{n+tr(S)}{n-2-tr(S)}\right\} \tag{6}$$

where *tr(S)* is the trace of the hat matrix. The hat matrix maps the vector of observed values to the vector of fitted values.

The *AIC* method has the advantage of being more general in application than the CV statistics and it can be used to select between a number of competing models by taking into account the differences in the model complexity (Fotheringham et al., 2002).

There is some limited evidence of the application of the GWR technique in the crime literature (see for example, Cahill & Mulligan, 2007; Chainey & Ratcliffe, 2005; Malczewski & Poetz, 2005) where the approach was found to be of greater utility in its superior ability to capture local processes driving crime levels. In addition, GWR was found to offer a method by which the misspecification of global models could be examined (Cahill & Mulligan, 2007). In a study of violent crime in Portland, Oregon, Cahill and Mulligan, (2007) concluded that global regression approaches demonstrated an inability to capture local variations in ecological relationships and as a result this reduced their overall explanatory power. In a study of residential burglaries in London, Ontario, Malczewski and Poetz, (2005) identified the value of GWR was in its capacity to better guide crime prevention policies through more specific geographic targeting in different neighbourhoods of the city.

To compute the GWR models, specialist software (GWR 3.x software Fotheringham, et al., 2002) is employed using the data compiled from the database integration component of the methodology. Four models (two GWR models and two global ordinary least squares (OLS) models) are estimated and compared, the first for malicious hoax calls the second for suspicious fires. Each model will use the rate of fire incidents across SSs as the dependent variable and the 32 Census variables previously extracted as the explanatory variables. To determine the best subset of the explanatory variables the Akaike Information Criterion (AIC) procedure is used (Akaike, 1981). The GWR model is statistically compared to a global OLS model for evaluation purposes using the F-test and AIC values of both models as outlined in Fotheringham et al., (2002).

(5) Trajectory analysis

Group based modelling is a technique growing in popularity (Piquero 2008) for the analysis of longitudinal data. Nagin (2005) provides a very clear treatment of the technique and the modelling decisions. In the simplest terms, individual units of analysis (usually people) are assigned to one of a fixed set of groups. The group pattern, or trajectory, is a summary of some outcome measure over time. The groups are modelled using a third-order polynomial, but the coefficients of the linear, quadratic and cubic terms are allowed to vary. That is, if there are four groups, the trajectory modelling computes four sets of regression coefficients. Polynomial functions are highly flexible and can take on a wide variety of shapes with up to two turning points.

Group based modelling was developed for the study of individual offending patterns over the life course (Nagin & Land 1993), and as such the dependent variable is usually count data (e.g. the number of offences in a time interval). This means that the Poisson distribution is frequently used for these models. Moreover, because λ is usually low, there are often more zero counts than would be predicted by the Poisson probability distribution. Zero-Inflated Poisson (ZIP) models are used to overcome this feature.

A number of recent studies have applied the technique to spatial units (Groff, Weisburd & Yang 2010; Groff, Weisburd & Morris 2009; Weisburd, Morris & Groff 2009; Weisburd et al. 2004). All of these studies have used street segments as the unit of analysis. In examining spatial interactions they have relied on retrospective diagnostic evaluation (i.e. analogous to examining residuals) in order to ascertain whether or not spatial autocorrelation is present. Spatial autocorrelation is the tendency of observations to be influenced by nearby observations. This approach is defensible as long as spatial autocorrelation is considered to be a nuisance artefact of the data.

Differences with modelling spatial units

A spatial unit of analysis introduces two additional modelling considerations for trajectory modelling:

<u>The population at risk:</u> If the unit of analysis is individuals then comparing observations by counts (or crimes) is valid. But we do not expect this of spatial units, which are usually compared by rates. The question becomes: what is an appropriate denominator? Three candidate measures are explored, namely the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC) and the Cross Validation Error (CVE) each of which are introduced later as a component of the trajectory analysis results section.

The spatial nature of the units: Most spatial information has some degree of spatial autocorrelation, due to Tobler's First Law of Geography (Tobler, 1970), so this needs to be accounted for. The approach taken by Weisburd and colleagues has been to examine spatial autocorrelation in the groups *after* model estimation. This is valid if no spatial autocorrelation is detected. An alternative approach is to incorporate the spatial interactions in the model estimation. This is quite technically challenging and has not been attempted to date.

Group Allocation

Much of the literature uses the BIC (Schwarz, 1978) as the metric for evaluating the optimal number of groups. Recent research by Nielsen et al. (2011) suggests an alternative metric, *Cross Validation Error* (CVE), is superior. Using *leave-on-out* cross validation, they estimate trajectory groups for the sample using all observations but one. This omitted observation is then used to assess the prediction accuracy of the fitted model (i.e. Y_i is compared to $\hat{Y}^{[-i]}$). The average absolute difference between observation *i* and the fitted values is CVE(*i*):

$$\mathrm{CVE}(i) = \frac{1}{T}\sum \mid Y_i - \hat{Y}^{[-i]} \mid \qquad (7)$$

where *T* is the number of time points in the longitudinal data set.

This process is repeated *N* times (so every observation is "left out"). The final CVE value is the average of all CVE(*i*) values.

$$\mathrm{CVE} = \frac{1}{N}\sum \mathrm{CVE}(i) \qquad (8)$$

The appropriate number of groups is the one associated with the lowest CVE.

Population at risk

Rates of fire incidents need to be computed to make comparisons between the spatial units. Three different rate measures are used in the exploratory phase:

- population-adjusted rates–incidents per 100 residential population;
- youth-adjusted rates–incidents per 100 15–24 year olds; and
- dwelling-adjusted rates–incidents per 100 private dwellings.

For completeness, the raw counts of incidents are also modelled.

A number of issues emerge with the calculation of rates. First, a small number of suburbs have zero denominator counts, resulting in values of ∞, which breaks the estimation. These observations are removed from the analysis. Second, the dominant probability distribution for trajectory analysis is Poisson, which is useful for count data. The rates are no longer counts, so strictly speaking the Poisson is not appropriate. On the other hand, the excessive number of zeros is still a feature of the rate variables and needs to be taken into account in whatever modelling work takes place. To resolve this problem, all fractional values are rounded up (using a “ceiling” function) and termed *adjusted counts*. The distributions look very similar. This way we can still use the Poisson distribution to control for the presence of excessive zeroes.

Much to our surprise we found very little difference between the raw and adjusted counts. Our suspicion is that, like crime, there is a difference between offender residence and offence commission and offenders travel to commit crimes (Boggs, 1965). Consequently, we present trajectories based on raw counts.

Computational difficulties with suspicious fires

For reasons still not entirely clear, the trajectory analysis was unable to be completed for suspicious fires for the entire state of Queensland. There seemed to be an interaction between the sample size and the number of groups being estimated. Trajectory group estimates were possible for subsets of the state, but once the sample size (i.e. the suburbs) approached 1,500 observations and the number of groups increased, the algorithm failed to converge. There were no issues for hoax calls.

To overcome this limitation, for the suspicious fire data we restricted our attention to South East Queensland, comprising 813 suburbs.

Chapter 4: Results and Analysis

The results and analysis are presented in three parts that collectively reflect the main components of the methodology described in Chapter 3.

Database integration, geocoding, descriptive mapping and analysis

Queensland fire incident data (provided by the Queensland Fire and Rescue Service) for a period of 13 years (1st January 1998 to 31st December 2010) describing all calls for service under malicious hoax calls and suspicious fires categories was procured.

> Malicious hoax calls are coded in the fire database as: *malicious or mischievous calls including alarm activations and manual call points*. All data coded under this incident category form the basis of the subsequent analyses detailed in this report.
>
> Suspicious fires are coded in the fire database as: *incendiary, legal decision or physical evidence that indicated that the fire was deliberately set, suspicious and circumstances indicate the possibility that the fire may have been deliberately set, separate unrelated fires were found, or there were suspicious circumstances and no accidental or natural ignition factor could be found*. All data coded under these ignition factors form the basis of the subsequent analyses detailed in this report.

Of the 19,119 malicious hoax calls reported in the fire database a total of 19,051 (99.6%) possessed the necessary spatial reference (the map grid reference) and geographic precision (i.e. the map grid reference was complete and correct). In relation to suspicious fires, there were 19,916 reported in the fire database from which a total of 19,732 (99%) were geocoded. The subsequent analyses presented in the final report draw upon the geocoded data equating to 19,052 malicious hoax calls and 19,732 suspicious fire records.

The remainder of this section presents the results of a descriptive analysis of both malicious hoax calls and suspicious fires in relation to their spatial and temporal patterning and the association of such patterning to socio-economics across the State.

Descriptive mapping and analysis of malicious hoax calls

First we focus on an analysis of the temporal dynamics of malicious hoax calls before exploring the spatial and spatial temporal patterning of malicious hoax calls. Figure 4 depicts analyses of malicious hoax calls by year, month, day and hour to identify salient temporal trends. A number of broad observations can be made from the findings:

Annually: There is evidence of some annual variation in the number of malicious hoax calls reported, the highest being 2000 (1,753 calls), the lowest 2003 (801 calls), a difference of 952 calls or 119%.

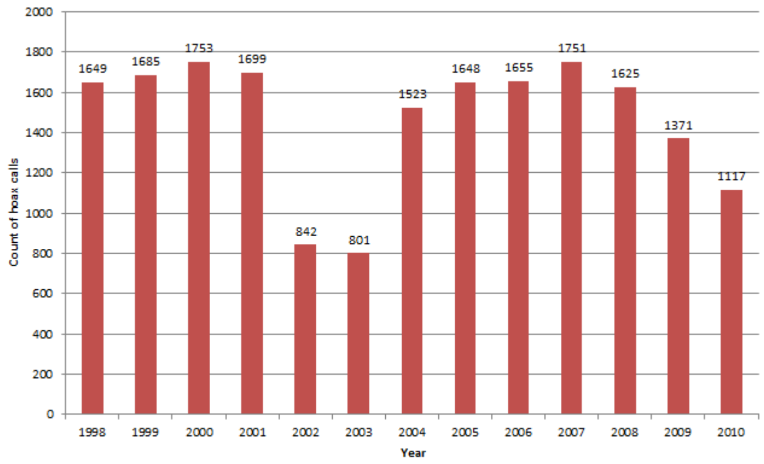
Monthly: There is evidence of marked monthly variation in malicious hoax calls, February being the quietest month, -15.41% below the monthly mean and October the busiest month 10.50% above the average. The monthly peak in October is both preceded (September: 3.69% above average) and proceeded (November: 1.50%) by months with above the average rate of malicious hoax calls.

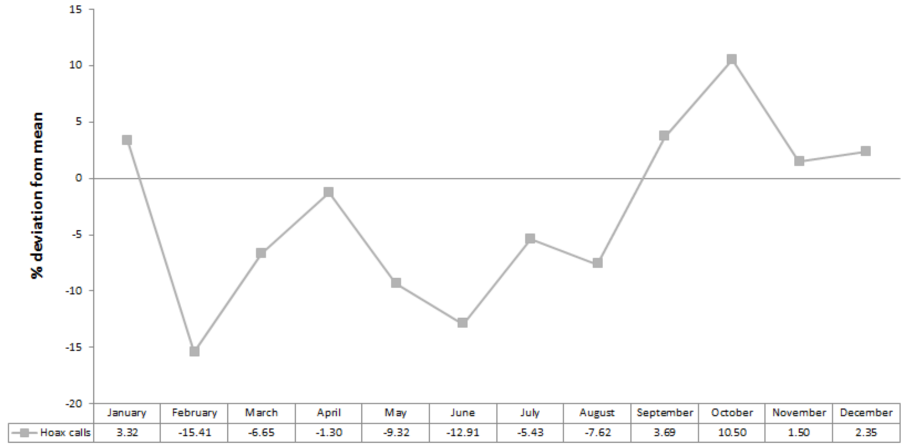
Daily: There is evidence of a distinct daily pattern with Saturday and Sunday experiencing malicious hoax calls at a rate 20% above the daily mean. Saturdays and Sundays are the busiest days at 38.39 and 21.34 above the mean daily rate. Tuesdays and Wednesdays are the quietest times for hoax calls, both falling below 15% of the daily mean.

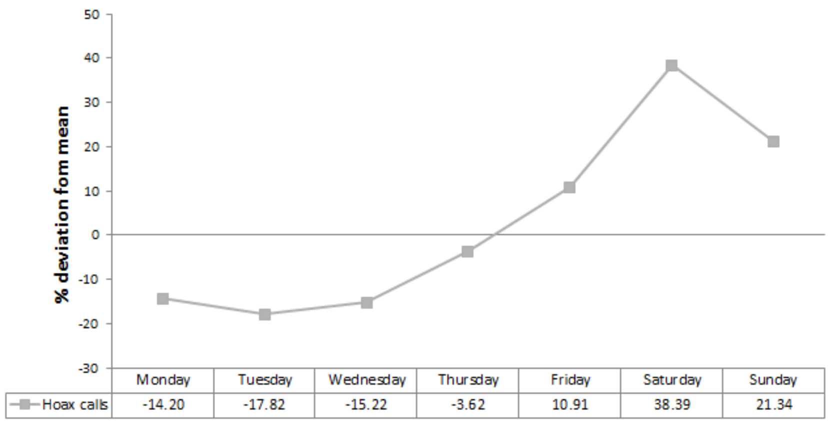
Hourly: Hourly patterns indicate the busiest times are in the late afternoon around 17:30 (67% above the mean hourly rate) followed by a small decline until around 18:30 (31.5% above the mean hourly rate). The observed incidence of malicious hoax calls drops below the mean hourly rate around 01:30 and remains below the line until 12:30 – i.e. this is the quietest times for malicious hoax calls. The quietest time is 06:30 that is 73.14% below the mean hourly rate.

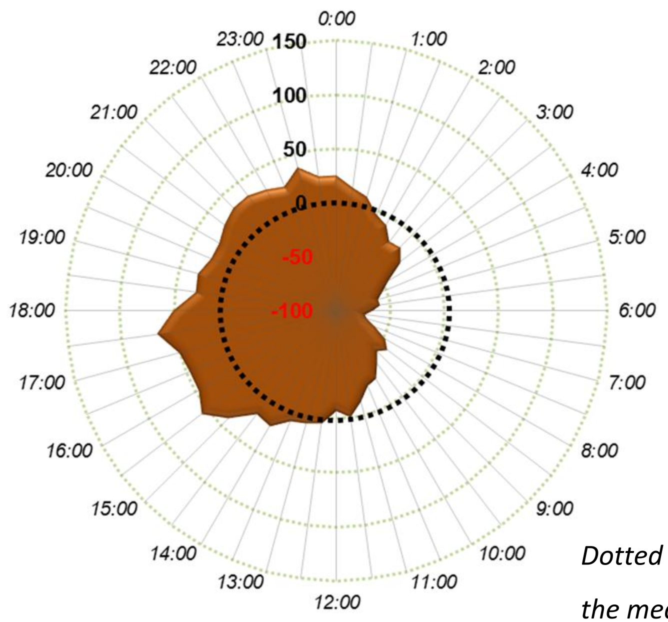
Next, looking at the influence of calendar events and specifically focusing on the weekday-weekend effect, Figure 5 depicts the degree to which the hourly distribution of malicious hoax calls is impacted. The median time that malicious hoax calls occur during weekdays is much earlier (5:59pm) compared to weekends (8:36pm) and a statistical test[4] confirmed that the hours at which malicious hoax calls occur between weekdays and weekends are significantly[5] different to one another.

[4] The Watson U^2 multi sample test for two circular distributions was used – see Mardia & Jupp, 2000, p.150.
[5] At the 99% level.









Dotted line represents the mean hourly rate

Figure 4: Temporal distributions of malicious hoax calls

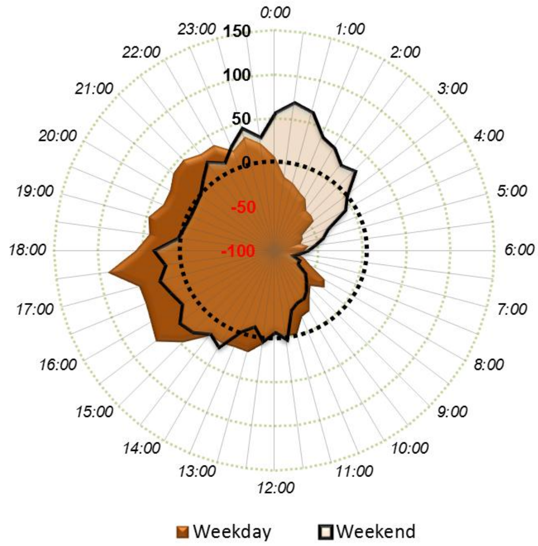


Figure 5: The Weekday-Weekend effect on the hourly distribution of malicious hoax calls

Next, we explore the spatial distribution of malicious hoax calls across the State. Figure 6 portrays the hotspot technique where the density of individual incidents per square kilometre are displayed. The output highlights a well-defined spatial pattern in which a number of specific areas can be identified as experiencing relatively high incidence of malicious hoax calls dominated by Brisbane and the South-East Queensland region. In addition, areas around Mount Isa, Townsville and to a lesser extent Cairns, Mackay, Bundaberg, Hervey Bay, Rockhampton and Toowoomba show evidence of elevated levels of malicious hoax calls. Combining the malicious hoax call data with population data to compute incident rates, Figure 7 highlights the degree to which the spatial distribution and population at risk is positively skewed – i.e. a limited number of suburbs have relatively high rates of malicious hoax calls. In fact, 50% of all malicious hoax calls across the State are located in suburbs that collectively account for 15% of Queensland's population.

Focusing on the types of locales where malicious hoax calls occur (Figure 8), it is apparent that the largest category is shopping complexes (24.4% of all malicious hoax calls), followed by dwellings and apartments (collectively accounting for 19.5% of all malicious hoax calls) and finally on the street (referred to as road complexes) equating to 9.3% of the total hoax calls.

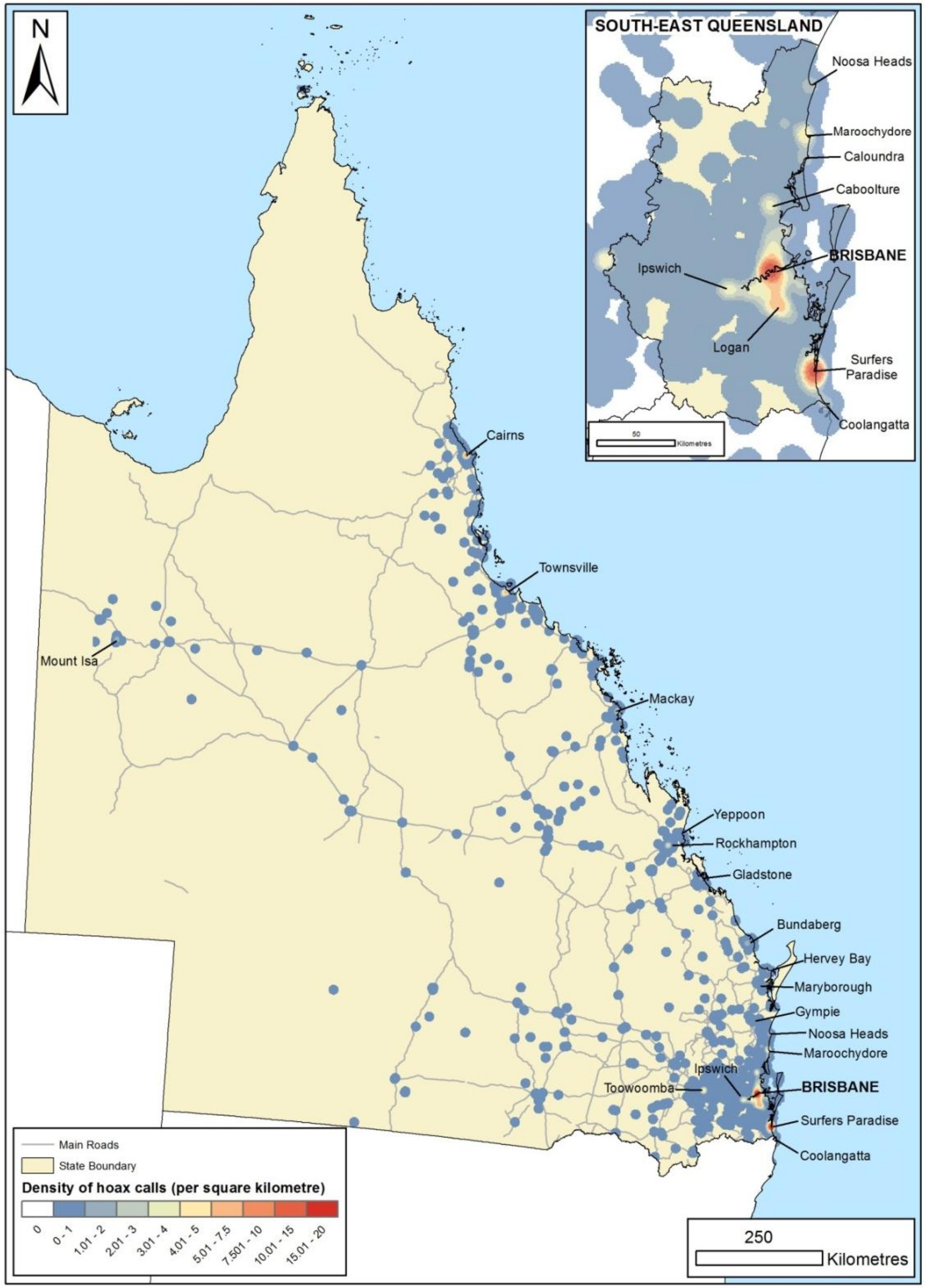


Figure 6: Malicious hoax call hotspot map

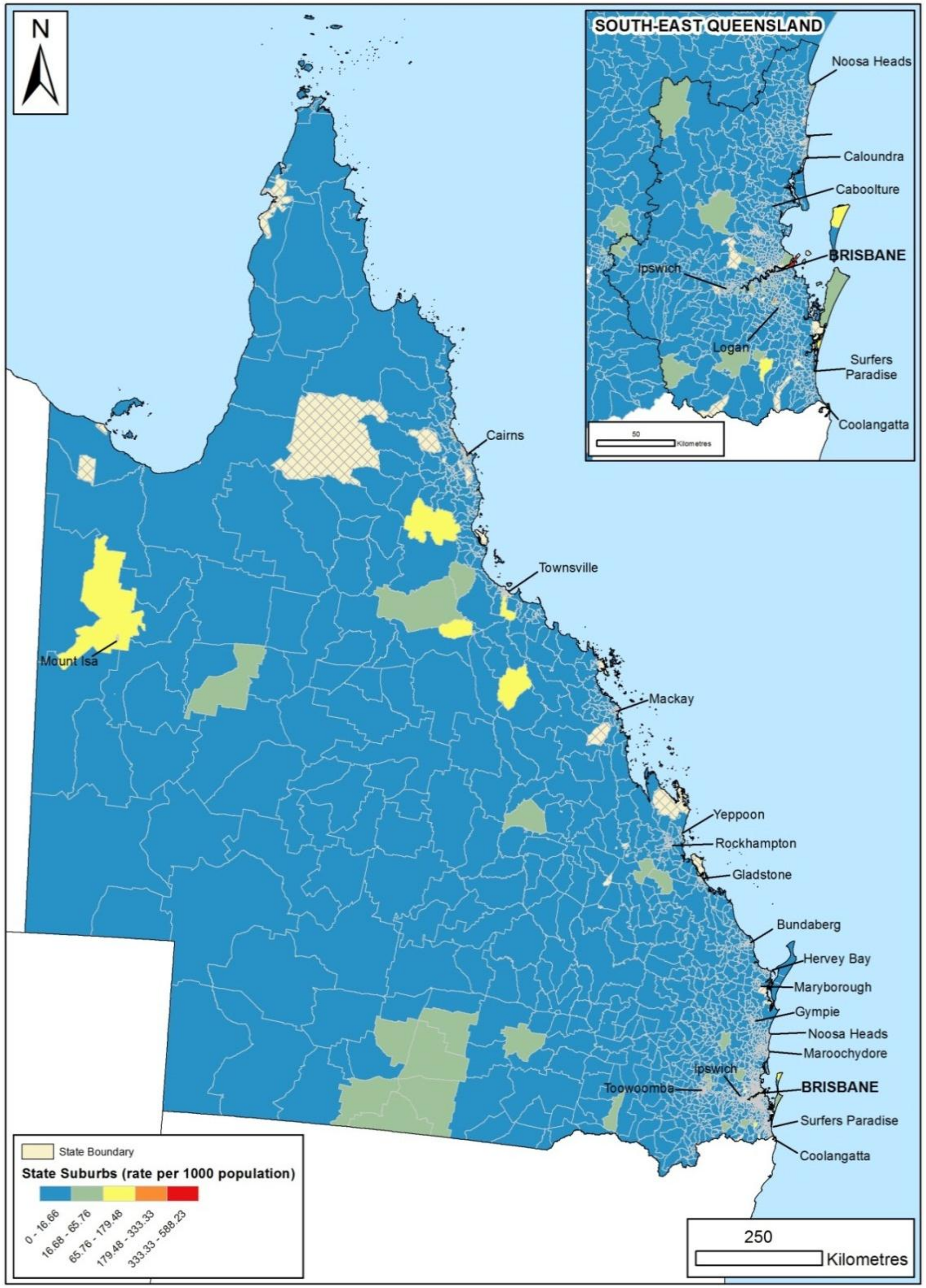


Figure 7: Malicious hoax call rate per 1,000 population

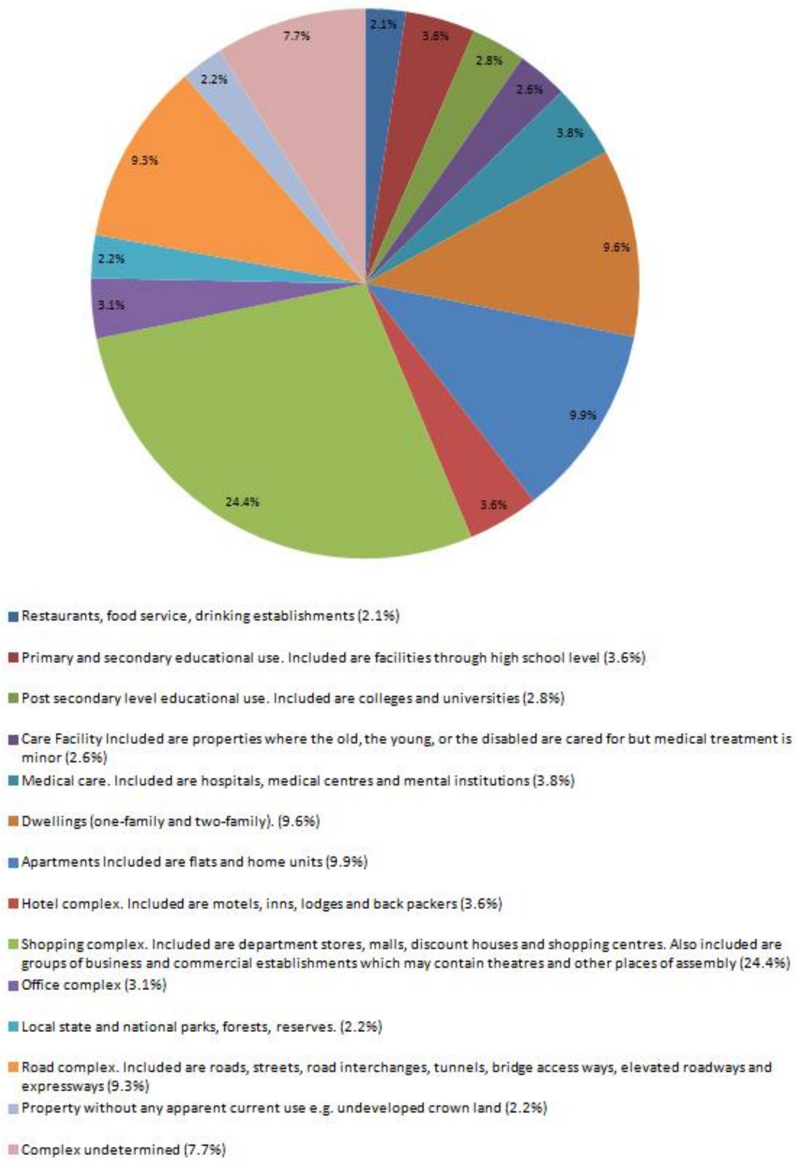


Figure 8: Malicious hoax calls by complex type

The final component of the descriptive exercise is to investigate clustering of malicious hoax calls in space and in space and time. To complete this task spatial clustering is first explored using the global Moran's I statistic to capture the degree to which there is evidence of positive (high incidence SSs adjacent to high incidence SSs – equating to an index value approaching 1) or negative (high incidence SSs adjacent to low incidence SSs – equating to an index value approaching -1) spatial autocorrelation. Computing the global Moran's I for each year over the 13 years provides information regarding changes in spatial arrangement (Figure 9). For malicious hoax calls (dark line) each year in the 13 year period is positively spatially autocorrelated with some evidence to suggest that the strength of this has increased over time.

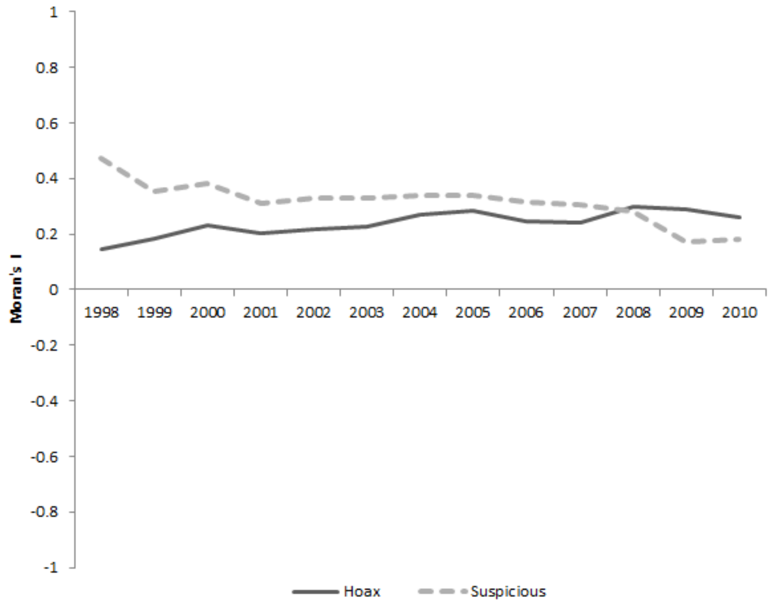
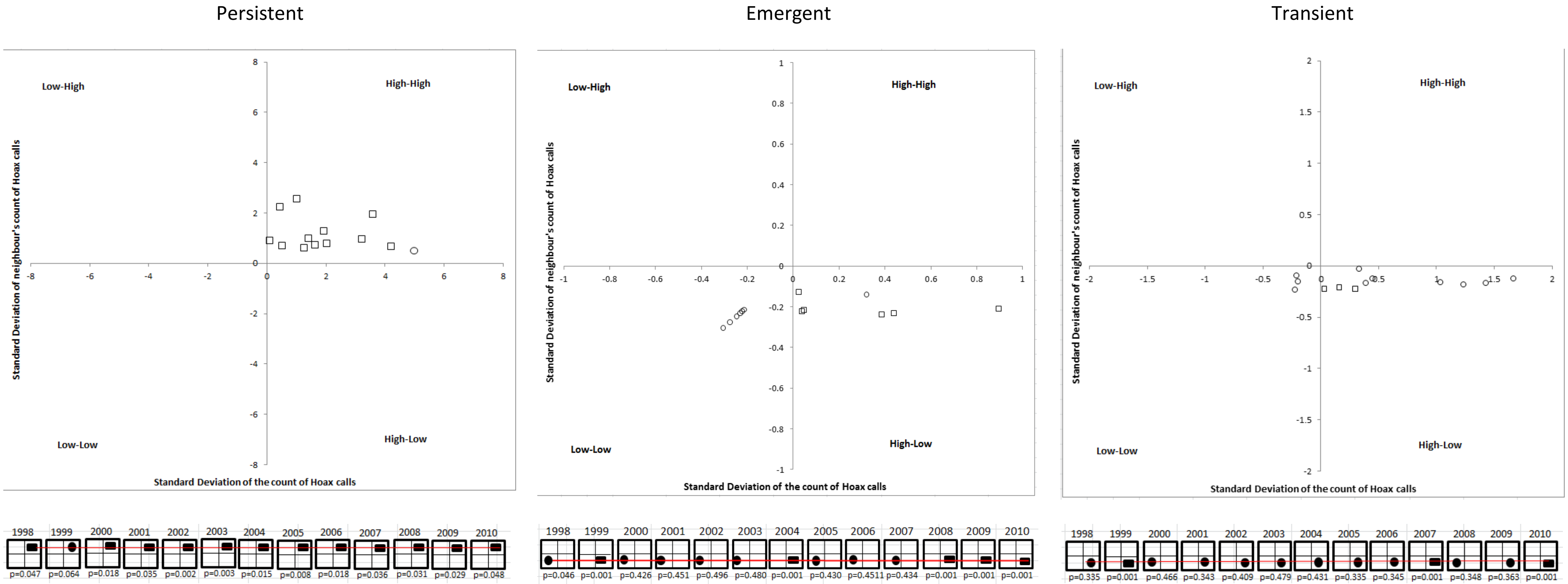


Figure 9: Change in global Moran's I statistic

To unpack this global relationship and explore local (SS-level) patterns of spatial arrangement we employ the local variant of the global Moran statistic. Here the *Moran scatterplot* and *Moran temporal plot* (described in detail previously) is used to explore changes in the spatial typology of a SS and help to perform a qualitative visual assessment of whether a SS might be considered, *persistent*, *transient* or *emergent*. In total there were 1,888 statistically significant transitions over the 13 years, which equated to 8% of the total possible transitions (23,580). The relatively low proportion of significant transitions (in relation to all possible transitions) was a function of either the SS not being a statistically significant cluster or outlier in either or one of the time periods. The highest number of SS transitions (849 or 45% of the total significant transitions) was high-high to high-high transitions equating to an 83% retainment rate, or in other words 83% of high-high SSs in the first time period remained high-high in the second time period. The smallest number of SS transitions were low-low (16 or 0.8%) with an 89% retention rate. The low-high outlier type was the second large transition type with 709 (38% of all transitions) that was associated with an 81% retention rate. Finally, the high-low type captured 144 or 8% of transitions with a 98% retention rate. Next, investigating the movement between cluster and outlier types, the largest change was observed between high-high (cluster) and low-high (outlier). Here there were 165 (or 9% of transitions) moves between low-high to high-high and 144 (8%) transitions between low-high and high-high. In summary, there is evidence of predominant local clustering (in particular high-high clusters) with a small strengthening of such spatial arrangement over the 13 years, supporting the evidence given in Figure 9.

Next, looking at individual SSs and using the *Moran temporal plot* to track the change in their spatial arrangement over the 13 years a qualitative visual assessment it made as to whether they can be considered *persistent*, *transient* or *emergent*. To enable the classification of SSs into one of the 3 types (in addition to a fourth category that captures SSs that fit none of the broad types) a heuristic is used that draws upon the number of statistically significant transitions across the 13 years.

A summary of these findings, using representative SSs for each typography is provided in Figure 10.



91% of significant transitions in the same type (high-high)

83% of insignificant transitions leading to 17% of significant transitions (high-low) in the final 3 years.

0% of significant transitions (3 significant individual periods each high-low), the remainder varying between low-low (cluster) and high-low (outlier).

Figure 10: Moran temporal plot, showing examples of *persistent, emergent and transient suburbs* for malicious hoax calls

Descriptive mapping and analysis of suspicious fires

First we focus on an analysis of the temporal dynamics of suspicious fires before exploring the spatial and spatial temporal patterning of suspicious fires. Figure 11 analyses suspicious fires by year, month, day and hour to identify any salient temporal trends. From this a number of broad observations can be made:

Annual: There is evidence of some annual variation in the number of suspicious fires reported. The highest number of incidents were recorded in 2002 (2,132 calls for service), the lowest in 2010 (452 calls for service), a difference of 1,680 calls for service or 372%.

Monthly: There is evidence of marked monthly variation in suspicious fires, February being the month with the lowest number of calls, -37.36% below the monthly mean and August the busiest month 35.19% above the average. The monthly peak in August is both preceded (July: 11.90% above average) and proceeded (September: 34.40% and October 28.26%) by months with above the average rate of suspicious fires.

Daily: There is a daily distinct pattern associated with suspicious fires. Saturday and Sunday are 40% above the mean mark (Saturdays and Sundays are the busiest days at 44.79 and 38.31 above the mean daily rate). Tuesdays and Wednesdays are the quietest times for suspicious fires at 13.37 and 10.78 below the mean daily rate.

Hourly: Hourly patterns indicate that suspicious fires most frequently occur in the late evening to midnight period, 23:30 to 00:00 (58.6% above the mean hourly rate). A steady decline in frequency is then evident until 03:00 when the observed incidence of suspicious fires drops below the mean hourly rate. From 03:00 it continues to drop until 07:00. The quietest time is 07:00 (74.94% below the mean hourly rate) and it is not until 13:00 that the observed incidence of suspicious fires rises above the mean hourly rate.

Next, looking at the influence of calendar events and specifically focusing on the weekday-weekend effect, Figure 12 depicts the degree to which the hourly distribution of suspicious fires is impacted. The median time that suspicious fires occur during weekdays is early (7:39pm) compared to weekends (8:53pm) and a statistical test[6] confirmed that the hours at which suspicious fires occur between weekdays and weekends are significantly[7] different to one another.

[6] The Watson U^2 multi sample test for two circular distributions was used – see Mardia & Jupp, 2000, p.150.
[7] At the 99% level.

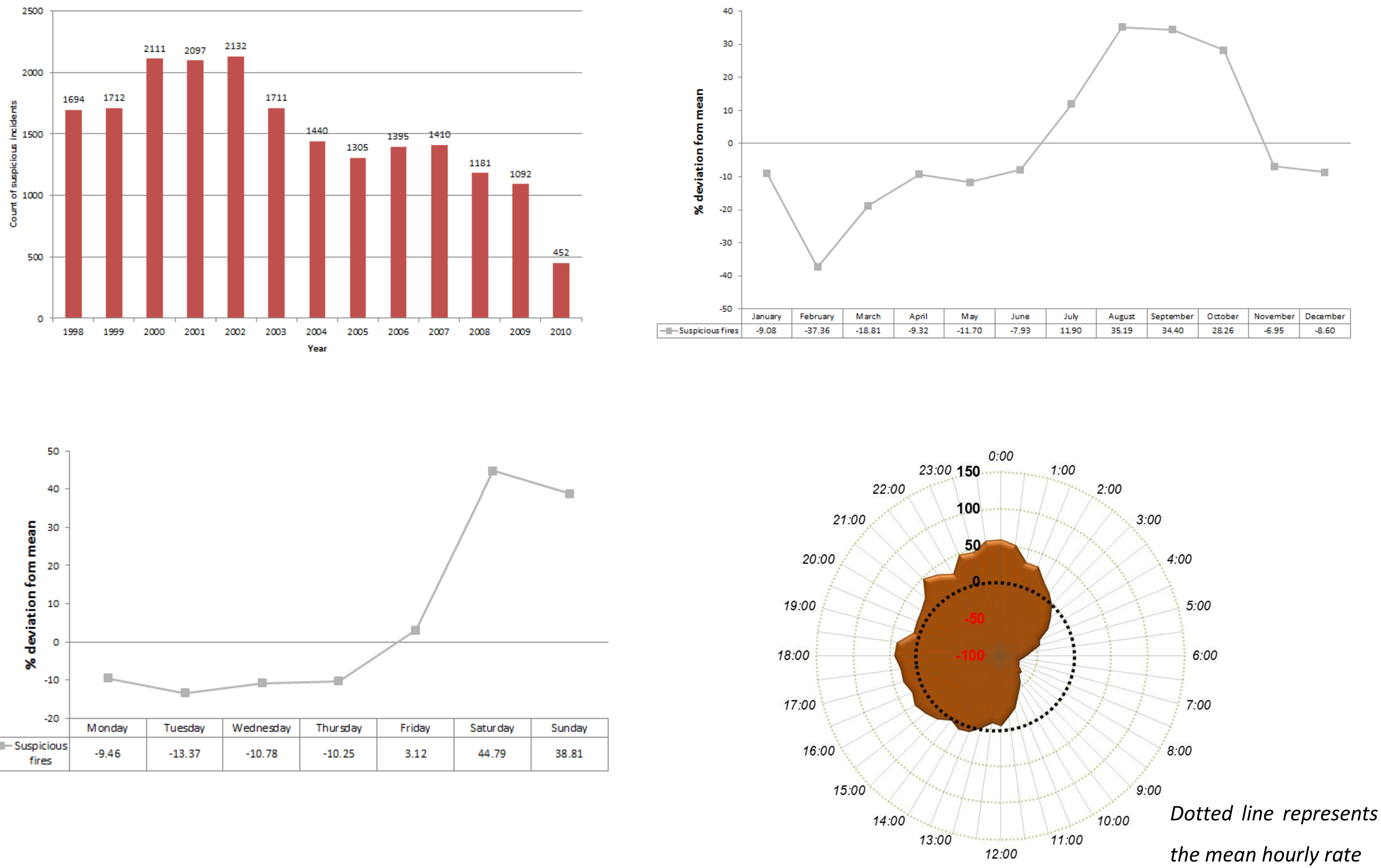


Figure 11: Temporal distributions of suspicious fires

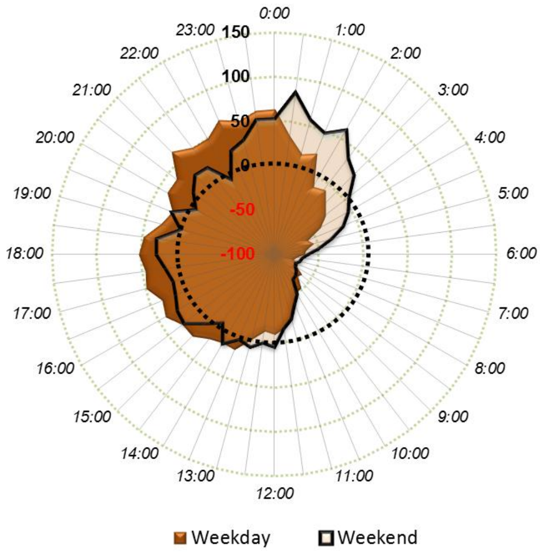


Figure 12: The Weekday-Weekend effect on the hourly distribution of suspicious fires

Figure 13 depicts the spatial distribution of suspicious fires across the state employing a hotspot technique that uses the individual incidents to generate a density of incidents per square kilometre. There is a well-defined spatial pattern in which a number of areas can be identified as experiencing relatively high incidence of suspicious fires that is dominated by Brisbane and the South-East Queensland region. In addition, areas around Mount Isa, Townsville and to a lesser extent Cairns, Mackay, Bundaberg, Hervey Bay, Rockhampton and Toowoomba show evidence of suspicious fire hotspots. By combining the suspicious fire data with population count data to compute incident rates, Figure 14 highlights the degree to which the spatial distribution and population at risk is positively skewed – i.e. a limited number of suburbs have relatively high rates of suspicious fires. In fact, 50% of all suspicious fires across the State are located in suburbs that collectively account for 33% of Queensland's population.

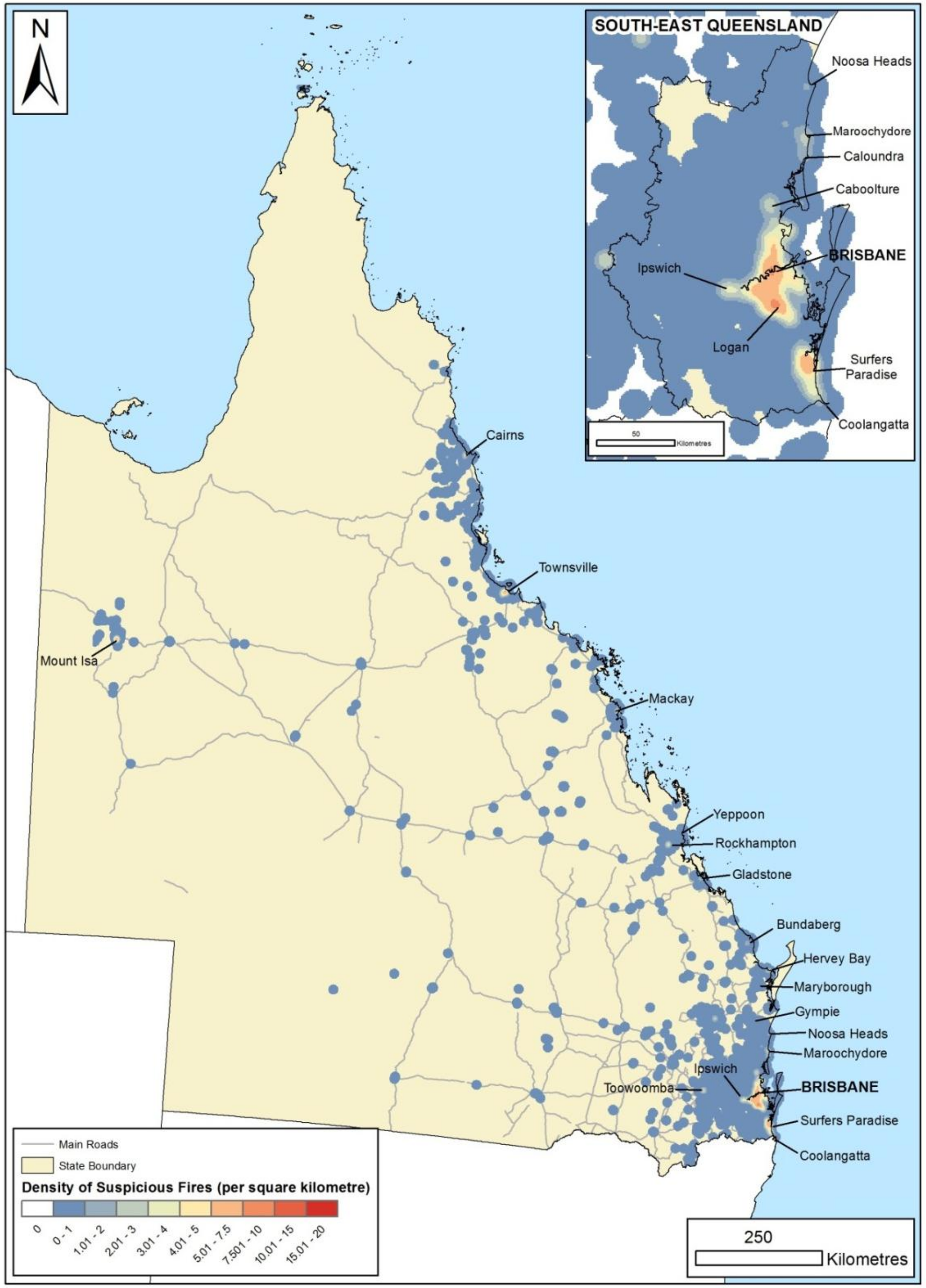


Figure 13: Suspicious fire hotpot map

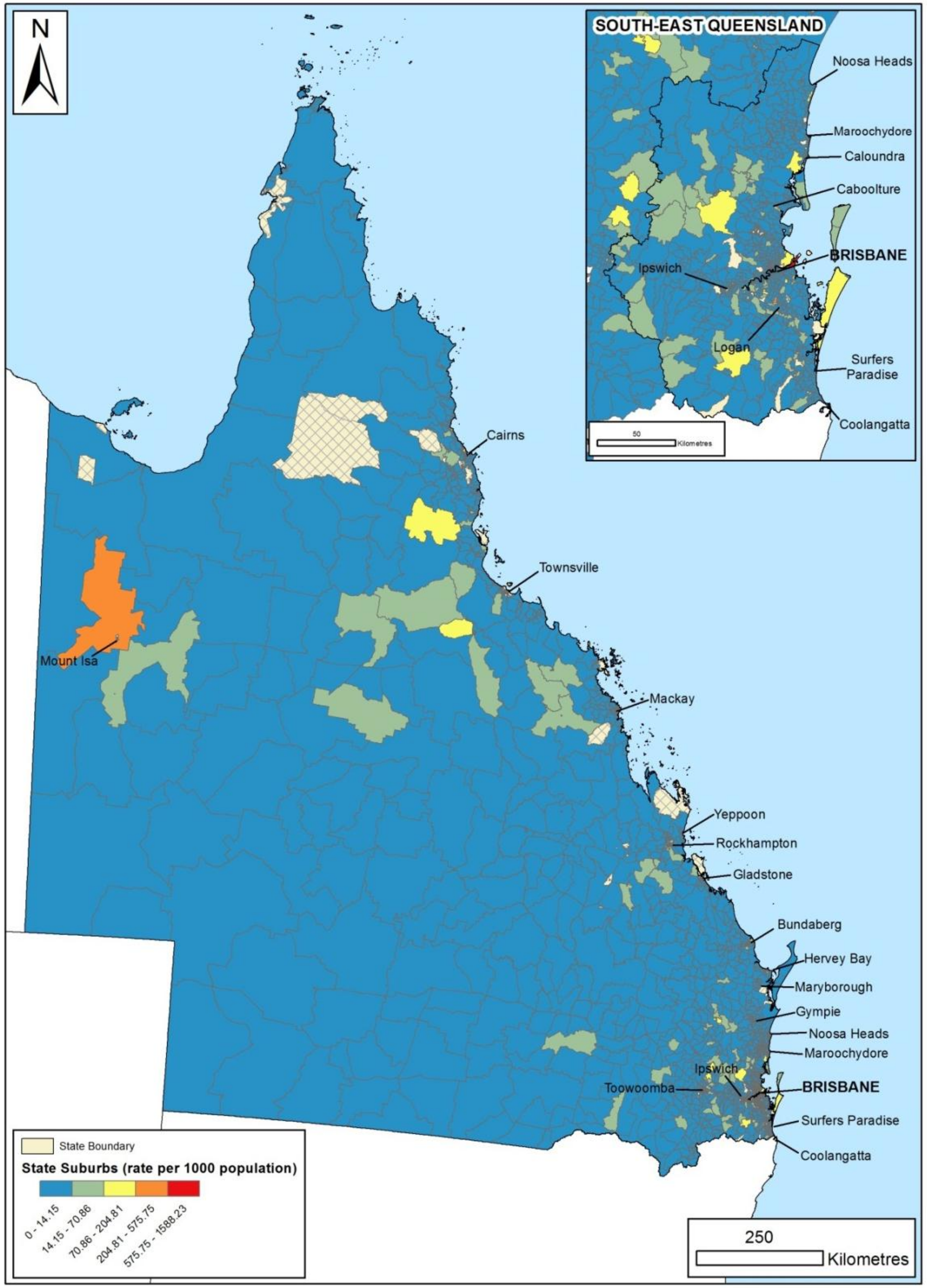


Figure 14: Suspicious fire rate per 1,000 population

Next, investigating suspicious fires by the complex type in which suspicious fires are recorded, Figure 15 depicts the largest category to be road complexes (equating to 17.4% of all suspicious fires), followed by dwellings (15.8%), local and national parks (15.1%) and within properties with no apparent use (15%).

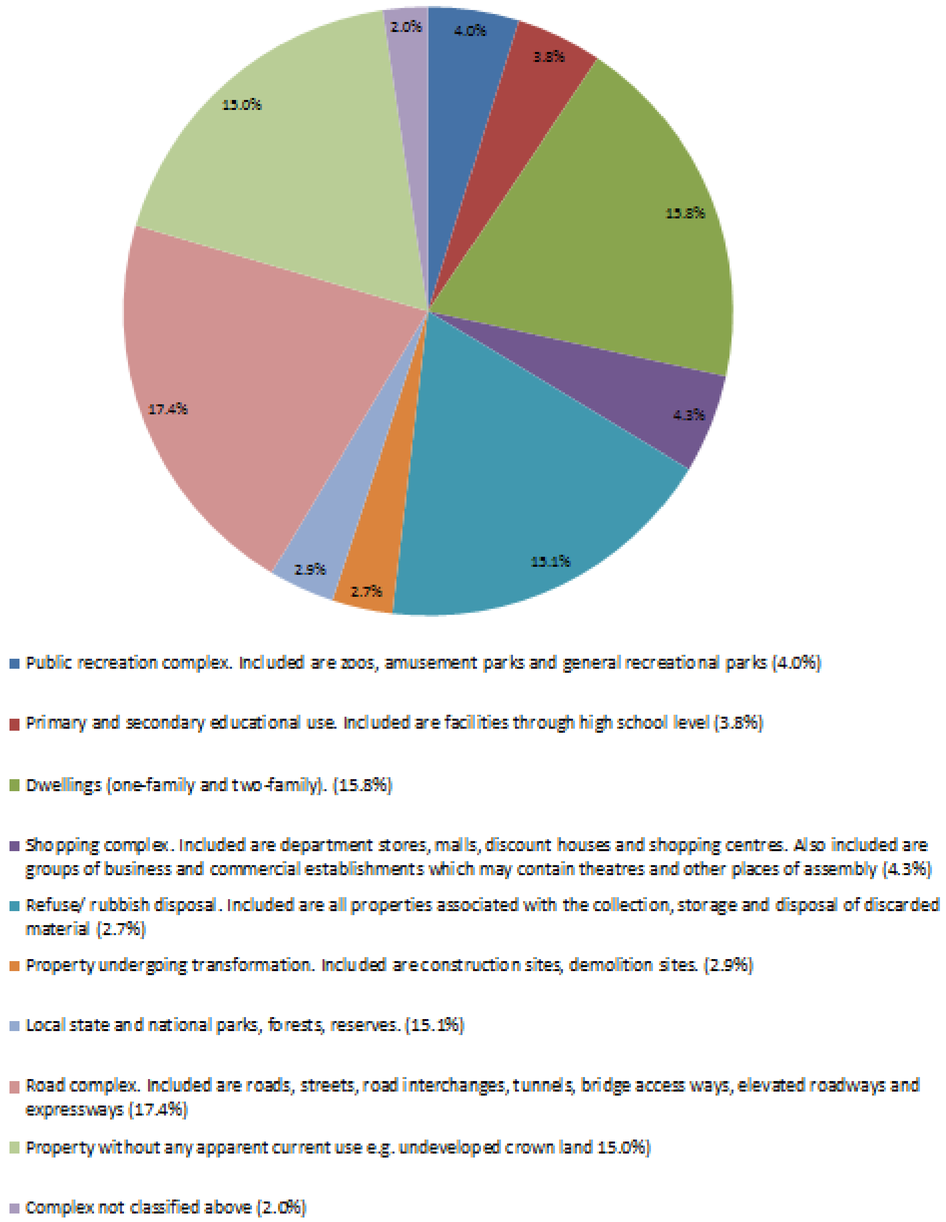


Figure 15: suspicious fires by complex type

The final component of the descriptive exercise investigates clustering of suspicious fires in space and in space and time using the global and local variants of the Moran's I statistic. First, computing the global Moran's I for each year over the 13 years (see Figure 9), highlights that for suspicious fires (dashed line) each year is positively spatially autocorrelated with the proceeding year. Further, there is some evidence to suggest that the strength of this association has decreased over time – i.e. the spatial association has tended towards a more random distribution with the I value approaching 0.

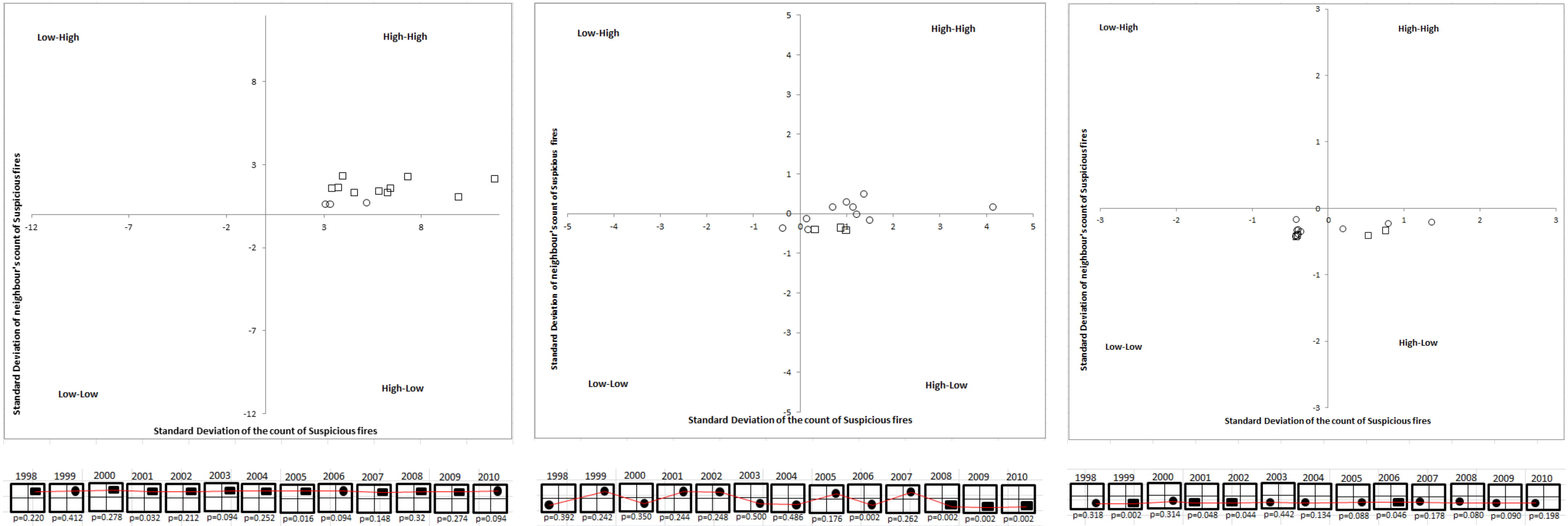
Next, exploring the local (SS-level) patterns of spatial arrangement the *Moran scatterplot* and *Moran temporal plot* is used to explore changes in the spatial typology of a SS and help to perform a qualitative visual assessment of whether a SS might be considered, *persistent*, *transient* or *emergent*.

In total there were 1,773 statistically significant transitions over the 13 years, which equated to 7.5% of the total possible transitions (23,580). The highest number of SS transitions (966 or 54% of the total significant transitions) was high-high to high-high transitions equating to an 84% retainment rate. The smallest numbers of SS transitions were high-low (99 or 5.6%) with an 85% retention rate. The low-high outlier type was the second largest transition type with 198 transitions (11% of all transitions), associated with only a 54% retention rate. Finally, the high-low type captured 123 or 7% of transitions with an 89% retention rate[8]. Next, investigating the movement between cluster and outlier types, the largest change was observed between high-high (cluster) and low-high (outlier). Here there were 184 (or 10.4% of transitions) moves between high-high to low-high and 166 (9.4%) transitions between high-high and low-high. In summary, there is evidence of local clustering (in particular high-high clusters) with a small weakening of such spatial arrangement (greater movement to outliers) over the 13 years, supporting the evidence in Figure 9.

Next, looking at individual SSs and using the *Moran temporal plot* to track the change in their spatial arrangement over the 13 years a qualitative visual assessment is made as to whether they can be considered *persistent*, *transient* or *emergent*. A summary of these findings is provided in Figure 16 through selecting representative SSs under each of these broad typographies.

[8] Retention rate is the term given to the proportion of significant transitions remaining with the same quadrant of the Moran temporal plot – i.e. the suburb experience no change, remaining part of either a significant spatial cluster (high-high or low-low) or a significant spatial outlier (low-high or high-low).

Persistent | Emergent | Transient



64% of significant transitions in the same type (high-high)

82% of insignificant transitions leading to 18% of significant transitions (high-low) in the final 3 years.

9% of significant transitions (low-low), the remainder of transitions not significant and vary between low-low (cluster) and high-low (outlier).

Figure 16: Moran temporal plot, showing examples of *persistent, emergent and transient suburbs* for suspicious fires

Summary of descriptive mapping and analysis

For malicious hoax calls and suspicious fires there are particular times and locations that experience elevated levels of each type of fire incident. Both incident types exhibit a relatively high degree of spatial and temporal skewness in which particular locations and times experience the majority of incidents.

From a theoretical perspective, the application of the place-based theories (such as routine activities theory (Cohen & Felson, 1979)) can help us to better understand the aforementioned patterning. Routine Activities Theory (RAT) states that individuals follow strict routines within which certain opportunities and risks are present in respect to criminal activities. In this project we explore the use of a variety of spatial and statistical techniques that have the collective capacity to help highlight the outcomes of activities undertaken by individuals in particular places in response to hourly, daily and monthly routines.

From the RAT perspective the notion of locality (and time) is central in comprehending the mechanics and patterning of criminal activity. To explore this theme the application of GIS tools has been used to identify salient criminogenic characteristics such as a concentration of malicious hoax calls within shopping complexes for example. Overall, the analysis has highlighted the relatively high degree of spatial and temporal skewness in malicious hoax calls and suspicious fires and more importantly identifies high incident places and times that may be the subject of further investigation.

Spatial Modelling

In the previous analytic component a series of descriptive geographic (i.e. choropleth and hotspot mapping) and temporal techniques (i.e. plots to capture annual, monthly, daily and hourly variations incidents) were applied to both malicious hoax calls and suspicious fires to explore their broad spatial and temporal dynamics over the 13 year data window. In addition, the types of locales in which both incidents typically occurred were investigated and we explored spatial autocorrelation (i.e. the tendency of observations to be influences by nearby observations) both globally (as a summary of the entire study region) and locally (at the suburb scale) through the *Moran temporal plot*. Next, continuing in the theme of a geographically orientated approach this section now progresses the previous descriptive analyses by entering into a spatial modelling exercise. Here we draw on Census data and combine these with the fire data in order to investigate the socio-economic and demographic drivers that explain the previously observed variations in both incident types.

Two modelling approaches are used here: Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models were developed using the total number of fire calls (over the period 1998 to 2006) within each SS, as the dependent variable, and the 34 ABS Census data variables (described in Table 2) as the independent variables. Separate models for malicious hoax calls and suspicious fires were computed. From the starting list of independent variables, a process of statistical elimination resulted in the selection of nine independent variables for the final model (listed in Table 3). These were age, ethnicity, family composition, qualifications, income, housing tenure, housing types and living stability. Variables including 'unemployment rate' were eliminated given that they were highly correlated with other independent variables thus impacting the overall robustness of the final model.

Given that the dependent variable (total number fire incidents) is typically a low-valued integer and there are frequent cases of very few fire calls for SSs across the study region, the use of a linear model was deemed inappropriate to explain such variation given that the error term was a non-normal distribution. This was most likely caused by the degree of heteroscedasticity present in the analysis. To remedy this issue the dependent variable was modelled as a Poisson random variant and then regressed against the independent variables. A Poisson GWR model is regarded as more appropriate, providing a count-based distribution model that improves the normality of the data's distribution (Fotheringham et al., 2002). The Poisson GWR models were formulated as:

Malicious hoax call model:

$$Ln(FC)(i) = ß0(i) + ß1(i)Teen1524 + ß2(i)OnePar + ß3(i)Moved + ß4(i)NonEsh + ß5(i)UnOcup + \varepsilon(i), \quad (9)$$

Suspicious fire model:

$$Ln(FC)(i) = ß0(i) + ß1(i)OnePar + ß2(i)HiQual + ß3(i)MeIncom + ß4(i)NonEsh + ß5(i)OwnDwel + \varepsilon(i), \quad (10)$$

Only significant variables are contained in each GWR model. FC is the total fire calls in each type in an SS; *i* denotes the *i*th SS location in the study region; $ß_n$ is the coefficient for the variable *n*; $ß_0(i)$is the local intercept at location *i*; and $\varepsilon(i)$ is the error term remained at location *i*.

GWR is used to analyse the local relationships (coefficients) between the number of fire calls and each independent variables at the local level. Here, an adaptive kernel is used for the local regression to account for the irregular distance between the data observations (defined as the number of the nearest neighbours that is determined by minimising the AIC score of the model). The data within the kernel are weighted by their distance from the regression point (an SS centroid). Hence, the data points that are closer to the regression point are weighted more heavily in the local regression, with the weights decreasing with the distance from this location, following a Gaussian decay function. Thus, each individual SS (as a regression point) has a set of relationships defined in the local regression so that the resulting coefficient estimates vary across the study region.

Regression results

A statistical summary of coefficients estimated by the OLS and GWR models is provided in Table 3; only the significant variables are included[9]. There are at least four interesting observations that can be made here:

First, is that both the proportion of one parent families in a SS (OnePar) and the proportion of people in a SS that were born in a non-English speaking country (NonEsh) were the two variables that were significant predictors for both OLS and GWR models and for both malicious hoax calls and suspicious fires.

Second, is that some variables have a significant relationship to malicious hoax calls and suspicious fires in the OLS models, however they do not appear to be a significant factor

[9] Temporal changes in the structural variables used in both the OLS and GWR models were investigated. Drawing on 1996, 2001 and 2006 Census data it was concluded that no relationships between changes in fire calls for service and change in the Census variables (specifically, the structural variables used in the models) existed. As such no adjustments to the model presented here were deemed necessary.

explaining fire incidence at a local level (GWR-based model). This is particularly the case for the proportion of white persons in a SS (White), which is significant for both malicious hoax calls and suspicious fires in the OLS models and not significant in either of the GWR models.

Third, is that a number of variables in the GWR models have a strong relationship to the number of malicious hoax calls, whereas their relationship to suspicious fires is not significant, as well as the reverse being the case. For example, the proportion of young people in a SS aged between 15 and 24 (Teen1524) shows a significant relationship to malicious hoax calls, however it is not significantly related to suspicious fires.

Fourth, is that the coefficient of variables varies greatly across the large study region (evidenced by the lowest value and the highest value in the GWR models), and many variables show both negative and positive local relationships between the independent and dependent variables. These relationships are also depicted cartographically in FiguresFigure 18 in which the spatial distribution of the estimated relationships between the independent variables (coefficients) and malicious hoax calls and suspicious fires, respectively, is illustrated. Each figure clearly demonstrates that the independent variables exhibit a spatially-varied relationship to the number of fire calls across Queensland.

Independent variable (SS)	Model			
	OLS		GWR	
	Malicious hoax call Coefficient (t)	Suspicious fire Coefficient (t)	Malicious hoax call Min : Max Mean	Suspicious fire Min : Max Mean
Proportion of people aged between 15 and 24 (**Teen1524**)	4.55 (10.40)	-	-2.60 : 23.35 4.18	-
Proportion of one parent families (**OnePar**)	4.32 (11.51)	6.8 (7.55)	-2.28 : 19.84 4.93	0.07 : 14.50 6.65
Proportion of people who achieved a qualification above high school (**HiQual**)	-	-2.26 (-3.84)	-	-7.30 : 6.62 0.50
Mean household weekly income (**MeIncom**)	0.00 (2.42)	0.01 (6.52)	-	-0.016 : 0.021 0.004
Proportion of people who moved the house in the last five years (**Moved**)	1.36 (6.08)	-	-3.72 : 5.26 -0.01	-
Proportion of people who were born in a non-English speaking country (**NonEsh**)	6.01 (10.74)	8.11 (10.41)	-13.13 : 24.17 5.20	-19.73 : 23.6 4.85
Proportion of white people (**White**)	-1.78 (-9.77)	1.412 (3.29)	-	-
Proportion of dwellings that are owned or being purchased (**OwnDwel**)	-	-2.7 (-6.2)	-	-4.14 : 1.05 -1.57
Proportion of unoccupied dwellings (**UnOcup**)	1.47 (10.76)	0.644 (2.3)	-2.18 : 6.83 1.63	-[10]

Table 3: Explanatory variables for OLS and GWR models

[10] '-'denotes not significant

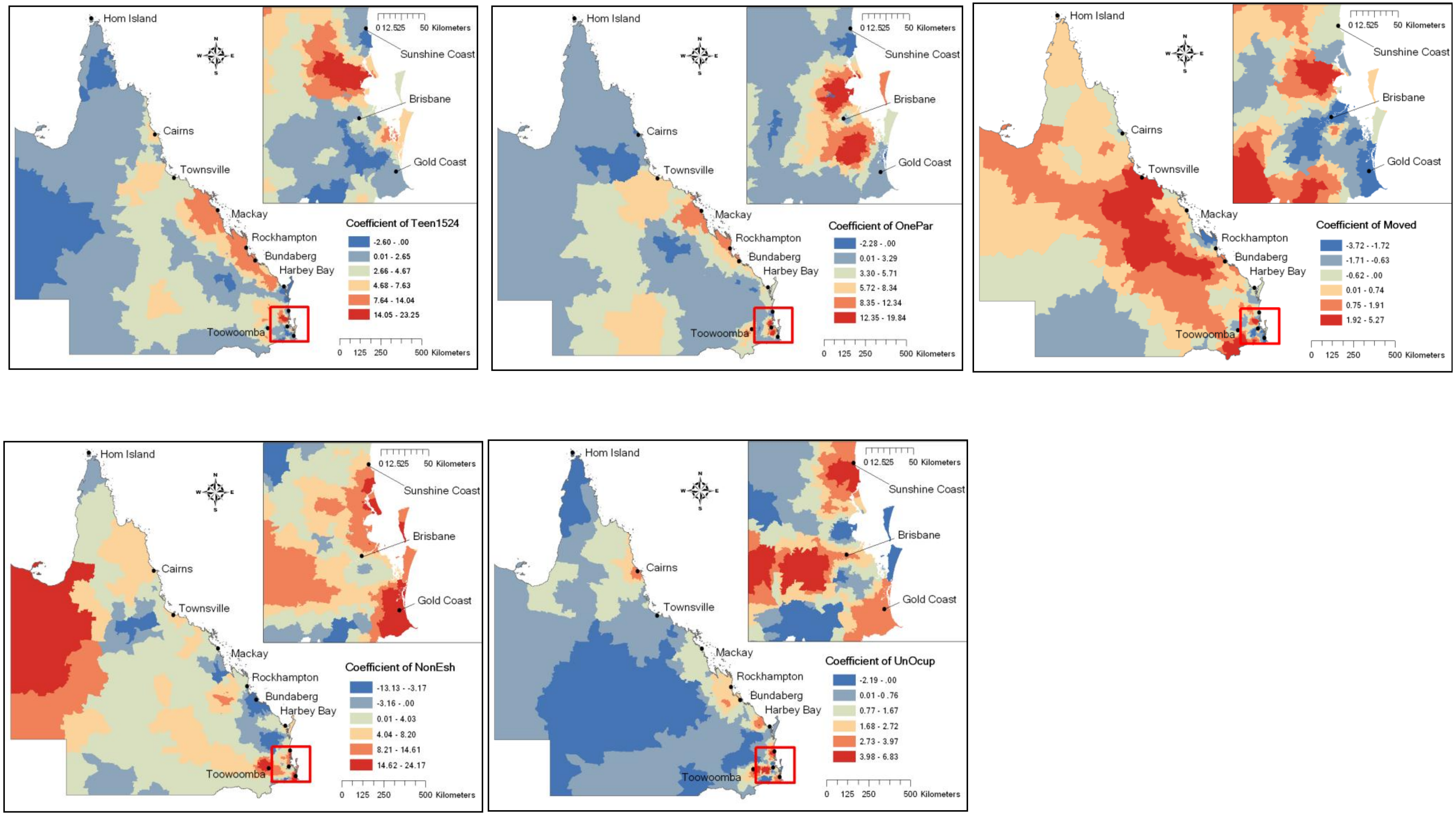


Figure 17: Spatial variation of coefficients for malicious hoax calls (GWR model)

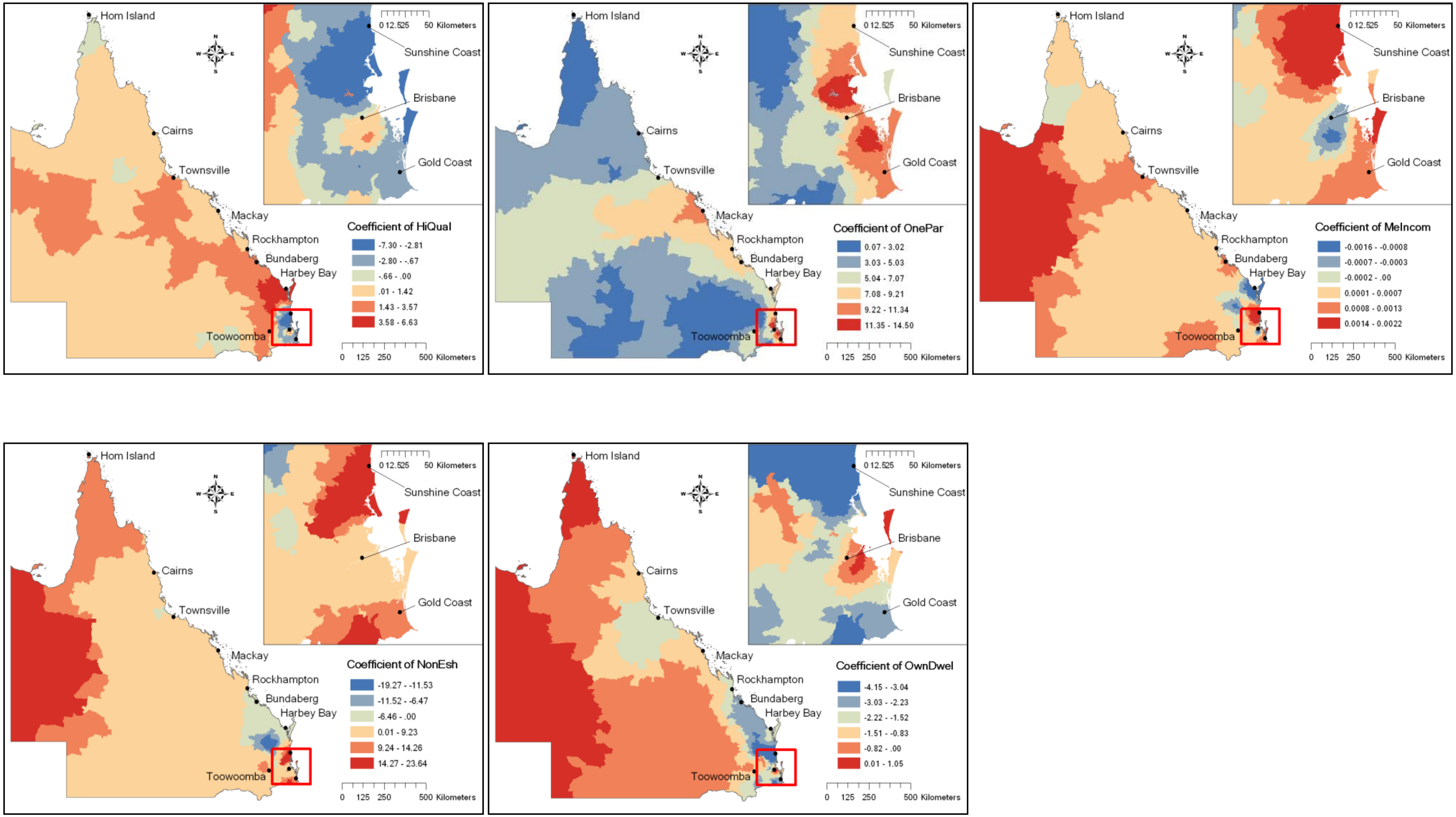


Figure 18: Spatial variation of coefficients for suspicious fires (GWR model)

The results of the analysis of variance (ANOVA) in which the OLS model is compared with the GWR model are given in Table 4. The results show that by accounting for the spatial non-stationary relationships, the GWR models offer an improved goodness-of-fit (when compared to the OLS model) for both malicious hoax calls and suspicious fires. The GWR model for malicious hoax calls presents a better goodness-of-fit than the GWR model for suspicious fires (measured by both *R* square and *AIC* statistics). In addition, the Moran's *I* statistics for residuals from each OLS and GWR model were calculated. The residuals from the OLS models show a moderate degree of positive spatial autocorrelation. In contrast, the Moran's *I* value of GWR models demonstrate that the residuals of GWR do not exhibit strong spatial autocorrelation. The GWR models in which spatial non-stationary relationships are incorporated into the modelling process have largely controlled the problem of spatially autocorrelated error terms (Moran's I: malicious hoax calls model = -0.012 and suspicious fires model = -0.014). This is not the case for both of the OLS models in which positive spatial autocorrelation remains in the residuals (Moran's I: malicious hoax calls model = 0.223 and suspicious fires model = 0.241).

	Malicious Hoax Calls		**suspicious fires**	
Summary of statistics	**OLS**	**GWR**	**OLS**	**GWR**
No. of Observations (SS)	1965	1965	1965	1965
No. of independent variables	7	5	7	5
No. of nearest neighbours (bandwidth)	-	279	-	135
AIC	-	5192.44	-	5456.58
R square	0.40	0.57	0.36	0.52
Spatial autocorrelation of residuals (Moran's *I*)	0.223	-0.012	0.241	-0.014

Table 4: AVONA results for the OLS and GWR models.

Summary of spatial modelling

The spatial modelling using GWR resulted in the generation of 2 models (one for malicious hoax calls and the other for suspicious fires) both of which have demonstrated higher levels of explanation (R squared values of 0.57 [malicious hoax calls] and 0.52 [suspicious fires]) than their OLS counterparts (R squared values of 0.4 [malicious hoax calls] and 0.36 [suspicious fires]), in addition to their mitigation of residual spatial autocorrelation issues. Finally, each GWR model drew upon five independent variables, in comparison to seven independent variables for both OLS models. Further, there were differences in the type of independent variables included in each of the final models. The capacity of the GWR models to offer enhanced explanatory power is best highlighted in Figure 17and 18. The findings depicted here clearly highlight the degree to which the coefficients vary both in size and sign. The equivalent OLS model computes an average value (as opposed to a location specific estimate as is the case with the GWR model) to capture a particular independent variable's variation in relation to the dependent variable. Whilst this is suitable in situations where location significantly impacts on that variable's capacity to consistently explain variation in the dependent variable, in circumstances where this is not the case it can create issues in the model's overall predictive capacity. Figure 17Figure 18 clearly indicate that there is geographic variation in each of the independent variables' capacity to explain the variation in the dependent variable for both the malicious hoax calls and suspicious fire models. This improvement in explanation is demonstrated through the higher R squared values for both GWR models over their OLS counterparts.

From a theoretical perspective, the role of 'place' is clearly highlighted in the GWR models. Each of the models (both malicious hoax call and suspicious fire models) highlight the spatially changing role of the various independent variables in their explanation of the variation in the dependent variable. From the RAT perspective the notion of locality is central in comprehending the mechanics and patterning of criminal activity. The spatial modelling in the current study highlights that 'space matters' for malicious hoax calls and suspicious fires and, more importantly, identifies the blend of 'location specific' factors that influence event patterning (i.e. the local mix of independent variables that used in combination can explain the variation of the dependent variable).

Trajectory analysis

The first step in the trajectory analysis is to establish the appropriate number of groups to use. In the absence of theoretical insight, the literature suggests this is performed in an incremental fashion estimating more groups until the BIC statistic asymptotes. In some circumstances this is problematic (see Nielsen et al., 2011), so we examined the BIC, AIC and CVE statistics.

Due to the well-known problem of spatial autocorrelation (Cliff & Ord, 1969; Townsley, 2009), there is a need to establish whether group membership is influenced by the membership of near suburbs. The conventional test of spatial autocorrelation, such as Moran's I (Moran, 1950) or Geary's C (Geary 1954), are not appropriate because group membership is a categorical variable. Instead, *join count tests* are available for testing spatial autocorrelation of categorical variables (Cliff & Ord, 1981; Goodchild, 1986; Upton, Fingleton, et al., 1985). Joins refer to the number of adjacent objects and are either same group or different group joins. The hypothesis tests examine whether or not, on average, the distribution of joins is in line with expectation. That is, is the count of same joins higher than would be expected if the groups were assigned randomly? There are two main types of join count test: within group tests (the number of same group joins) and between group tests (the number of different group joins). For each test the full set of combinations of group joins is computed (i.e. joins between group 1 and group 1, joins between group 2 and group 2, etc.).

Join count tests are sensitive to the definition of neighbour relations that are specified by the researcher. Unfortunately, there is little guidance in the literature on systematic ways to approach this step. There are two main decisions. First, the criterion of what comprises a neighbour: queen-style compared to rook-style neighbours, analogous to chess moves. Second, the weighting used to signify the extent of influence. We favour parsimony, and given there has been little prior work studying spatial processes of hoax fire calls and arson activity, the queen adjacency (reflecting that individuals can travel through space in a variety of directions), and a binary weighting scheme (all neighbours were considered equally influential) are used.

Previous spatial trajectory studies have used different methods to test spatial autocorrelation. The most sophisticated treatment can be found in Groff, Weisburd, and Yang (2010). Because their units of analysis are reasonably small, they converted the street segments into point data (i.e. they took the mid-point) and examined the following:

1. *within-group patterns*. Using Ripley's K they investigated the proximity of same group observations within set spatial intervals.

2. *inter-group patterns*. Using bivariate K function they performed pairwise comparisons for each group combination. j groups results in $\frac{j(j-1)}{2}$ tests.

These tests are analogous to join count tests but instead they count the number of group members *within a specified distance*. This is defensible for micro-units of analysis employed by Groff, Weisburd, and Yang (2010), but is unlikely to be appropriate for the units of analysis used in our study.

Groff, Weisburd, and Yang (2010) found that the same group trajectories all showed clustering for distances of less than a mile, but those groups hosting the highest crime had the strongest clustering patterns. Groff, Weisburd, and Yang (2010) classified spatial relationships between groups as *repulsion* (negative spatial autocorrelation), *independent* (no spatial autocorrelation) and *attraction* (positive spatial autocorrelation). They observed no repulsion relationships. For the purpose of this analysis we will replicate the approach outlined in Groff, Weisburd, and Yang (2010).

Hoax Calls

Establishing the Valid Number of Groups and Examining the Groups

Figure 19 shows that seven groups is the optimal number of groups for all three evaluation metrics.

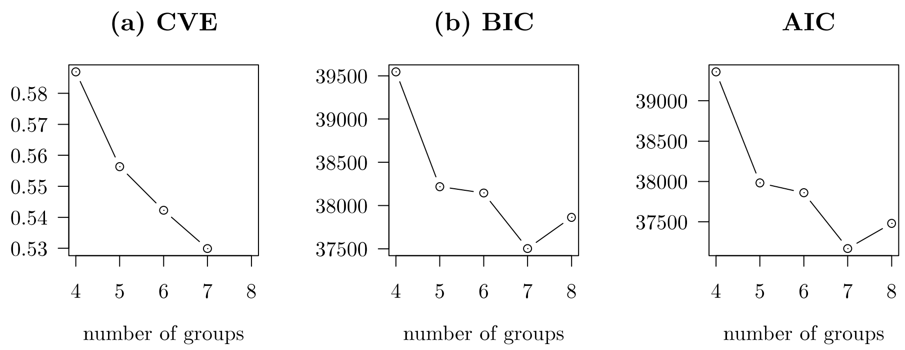


Figure 19: Number of Trajectory Groups using Hoax Calls

Figure 20 displays the seven estimated trajectories and their relative proportions. It is difficult to distinguish the individual trajectories of each group; particularly those with a low frequency of calls per year. In order to examine these in greater detail Figure 21 shows the observed longitudinal pattern of hoax calls (grey lines) alongside the estimated trajectory for the individual groups (indicated by the solid line). Note the limits of the y axis change from plot to plot.

The main difference between the groups is scale. The trajectories are all fairly flat and are located at different levels on the y-axis. There is a remarkable consistency in that each successive group is located about half the level of the previous group. For instance, Group 1 is a high volume but rare group, with an average number of hoax calls of about 50 per year. Group 2 fluctuates around 10 calls per year, and Group 3 around 5 calls per year, and so on.

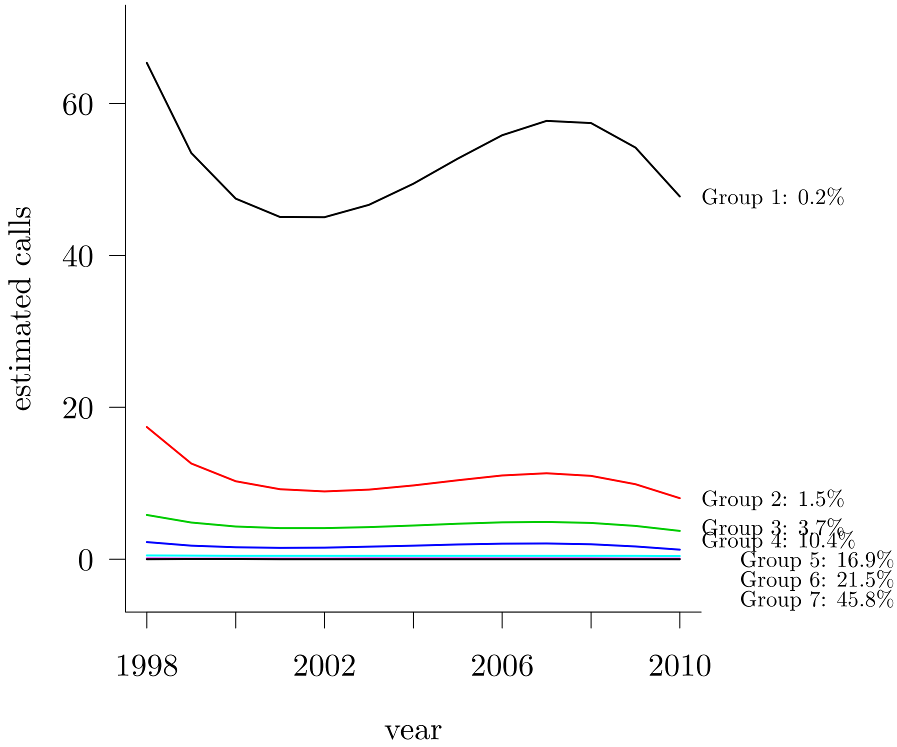


Figure 20: Group Trajectories for Hoax Calls

Group 7 displays some interesting characteristics. It accounts for nearly 45.8% of all observations, about 900 suburbs in all. The overall pattern during the time frame is zero calls for all years except for 29 suburbs, each with a single call in the year 2000.

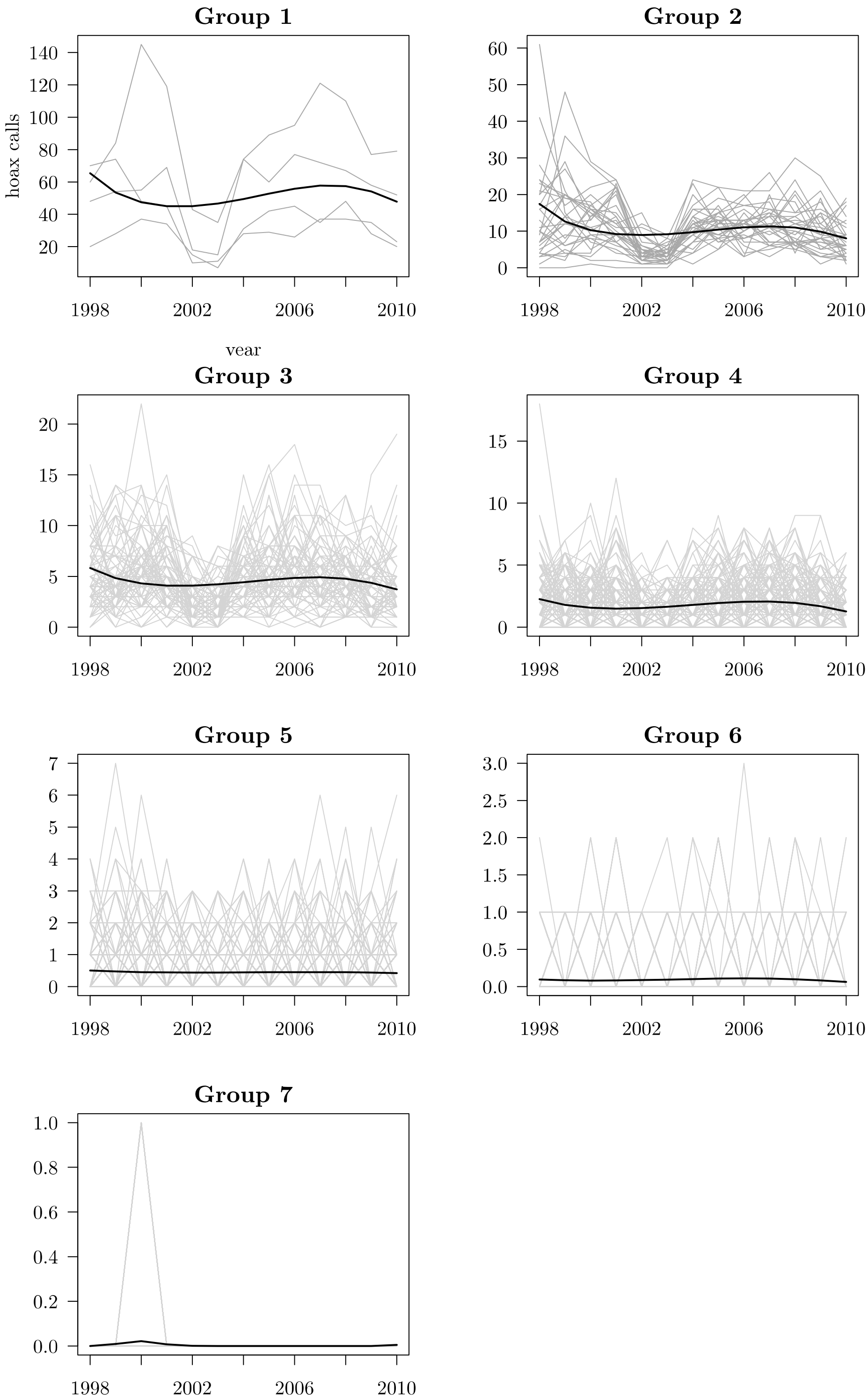
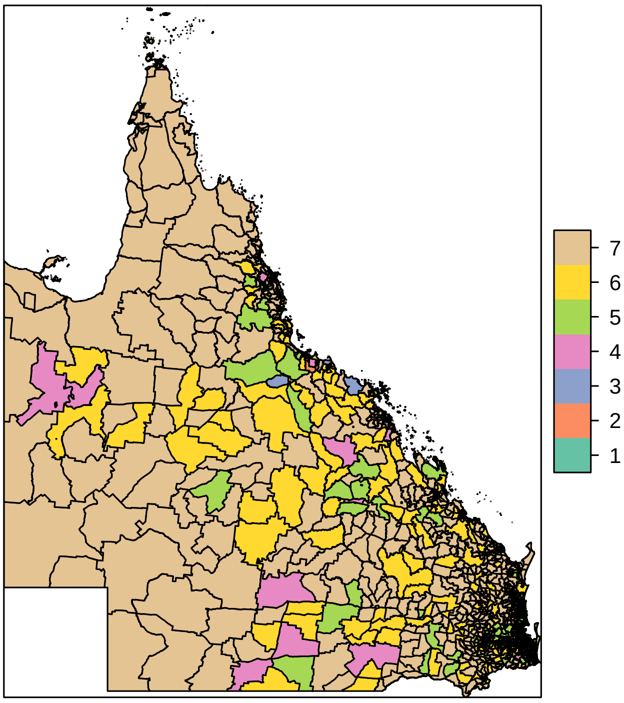


Figure 21: Trajectories for all groups (malicious hoax calls)

Spatial Patterns

Due to the spatial extent of the study region and the varying scales of the suburbs, the spatial patterns cannot be displayed in a single map. We break up the presentation across three maps, depicting the pattern at the broader State (Figure 22



), the South East Queensland region (Figure 23) and the finer Brisbane metropolitan area (Figure 24).

The depiction of group membership is dominated by Group 7 (the zero group, comprising nearly 45.8% of all observations), although this is likely an artefact of the *modifiable area unit problem* (Openshaw, 1983). When the focus shifts to finer resolutions, more variation emerges in the densely populated South East Queensland region (Figure 23), with groups 6 and 5 becoming more prevalent. Finally, concentrating on the Brisbane metropolitan region, Figure 24 depicts that all groups appear in the densely populated part of the study region, particularly Groups 2 to 5.

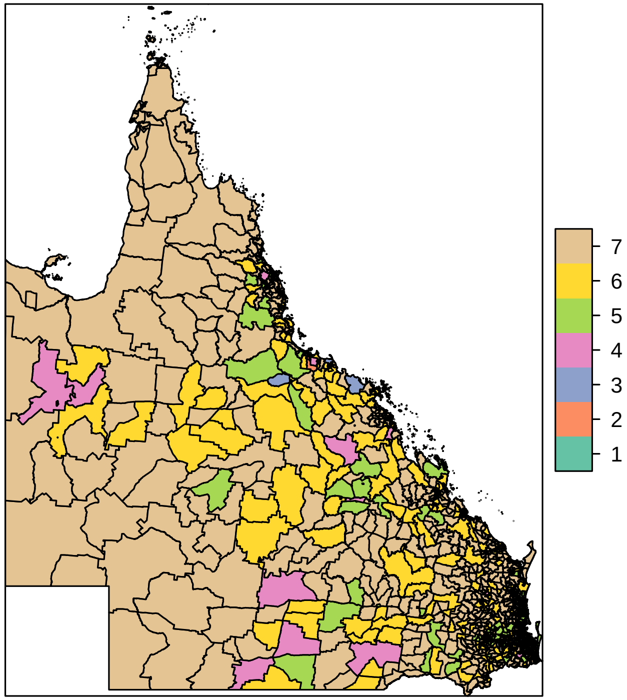


Figure 22: Map of Group membership across QLD (Malicious hoax calls)

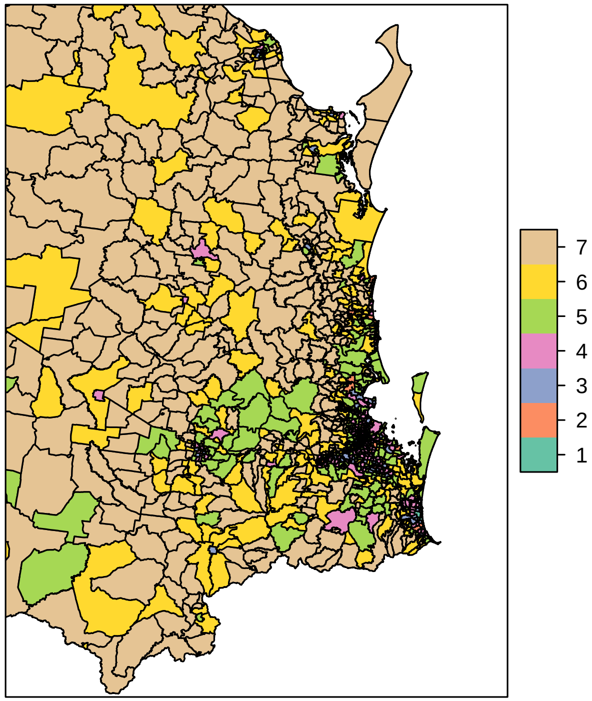


Figure 23: Group Membership across South East Queensland (Malicious hoax calls)

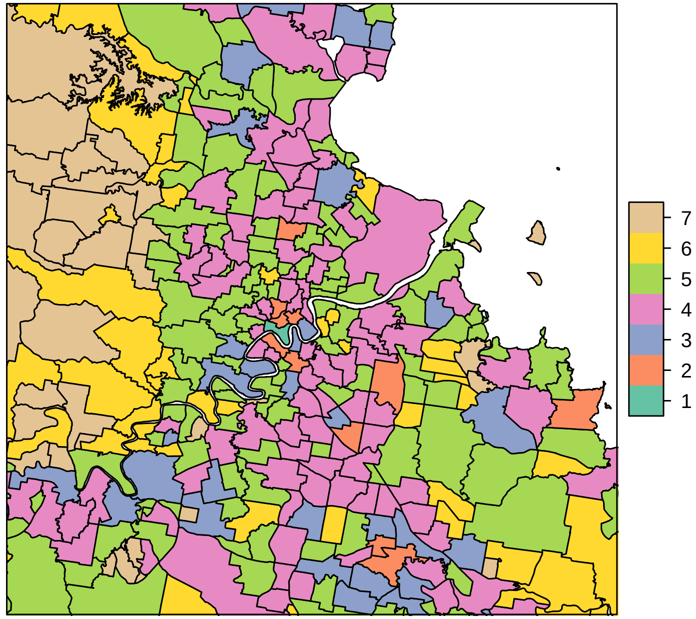


Figure 24: Group membership across the Brisbane metropolitan region (malicious hoax calls)

Spatial Autocorrelation

The results of the cross-K join count tests are shown in Figure 25. The *z* scores for each unique combination of group pairs are shown. Each number in the plot indicates a group combination, indexed by the y axis. So, the test of join count of Group 1 & 2 is represented by the "1" aligned with the *Group 2 joins* row. The join count of Group 3 & 4 is given by the "3" aligned with the *Group 4 joins* row. Same group join count tests are indicated by the numbers on the *same group joins* row. The vertical lines represent the p-value thresholds of 0.05 with a Bonferroni correction to account for the 29 comparisons being made.

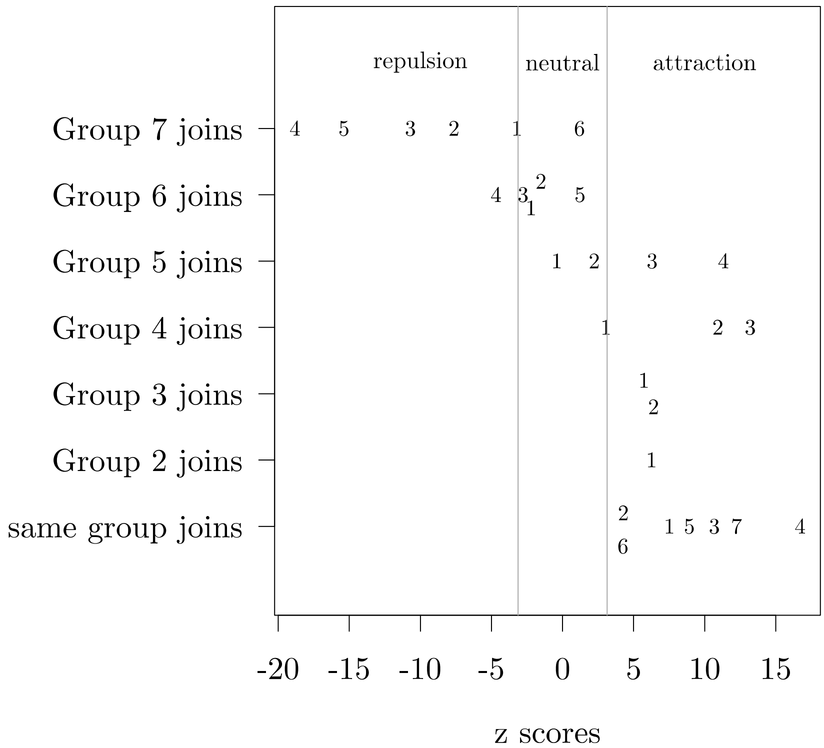


Figure 25: Results of k-group join count tests for malicious hoax calls

There is clear evidence that group trajectories exhibit spatial autocorrelation. The observed count of same group joins is greater than expected under the null hypothesis of random allocation *for all groups*. This means that groups tend to be located adjacent to each other to a greater extent than we would expect under the null hypothesis. This observation has two implications. First, the spatial autocorrelation observed is similar in nature to that found in studies focusing on other types of crime, such as burglaries and violence, as an outcome measure. That is, using similar methods for two distinct social phenomena we found similar results. The fact that suspicious fires and malicious hoax calls are entirely different behaviours yet displayed results similar to these other crimes patterns is remarkable. Second, as noted in the literature review suspicious fires and malicious hoax calls have rarely been considered from a criminological perspective despite the clear connections.

The results displayed here suggest that the dynamics involved with longitudinal spatial distributions of other crimes share characteristics associated with patterns of suspicious fires and malicious hoax calls. In addition, this is evidence that criminological theories may be suited or have renewed relevance in our conceptualisation of these sorts of fire related phenomena.

In terms of the join count results for different groups, using the repulsion, independent, attraction classification introduced by Groff, Weisburd, and Yang (2010), there are only a small number of the group that were independent (no spatial autocorrelation):

- Group 1 compared to 4, 5, 6, 7 separately;
- Group 2 compared to 5 and 6 separately; and
- Group 6 compared to 3, 5 and 7 separately.

The following group combinations exhibited repulsion (negative spatial autocorrelation):

- Group 6 compared to 4; and
- Group 7 compared to 2, 3, 4 and 5 separately.

The following group combinations displayed attraction (in addition to the same group combinations):

- Group 1 compared to 2 and 3 separately;
- Group 2 compared to 3 separately; and
- Group 4 compared to 2 and 3 separately.

The pattern in these results is that the high malicious hoax call suburbs tend to "hang" together, forming clusters or joins at a rate higher than expected under the null hypothesis. High malicious hoax call suburbs are "attracted" to other high malicious hoax call suburbs. Low malicious hoax call suburbs tend not to cluster together, however. The "medium" malicious hoax call suburbs tended to be located close to the low rate suburbs at roughly the expected level.

Suspicious fires

Establishing the Valid Number of Groups

Figure 26 shows contrasting results, with different minimum values for the three evaluation metrics. Given the documented problems with the BIC (Blokland, Nagin, & Nieuwbeerta, 2005; Loughran & Nagin, 2006; Nagin, 2005;), we elected to rely on the CVE metric. This indicated that six groups provided reasonable estimates. Again, these data were for South East Qld only.

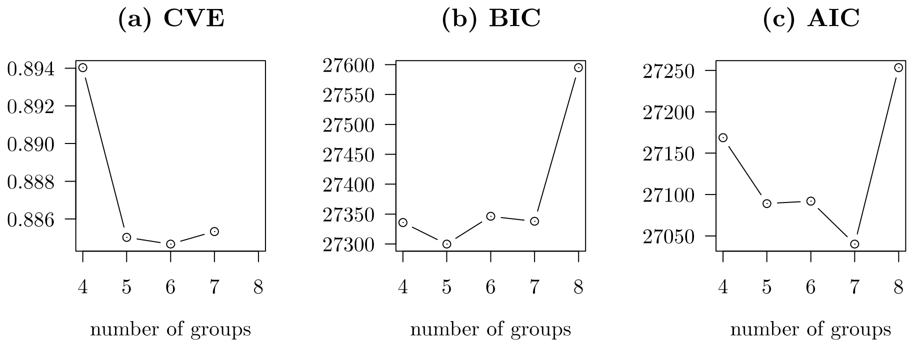


Figure 26: Number of trajectory groups across South East Queensland (suspicious fires)

Examining the Groups

Figure 27 displays the six estimated trajectories.

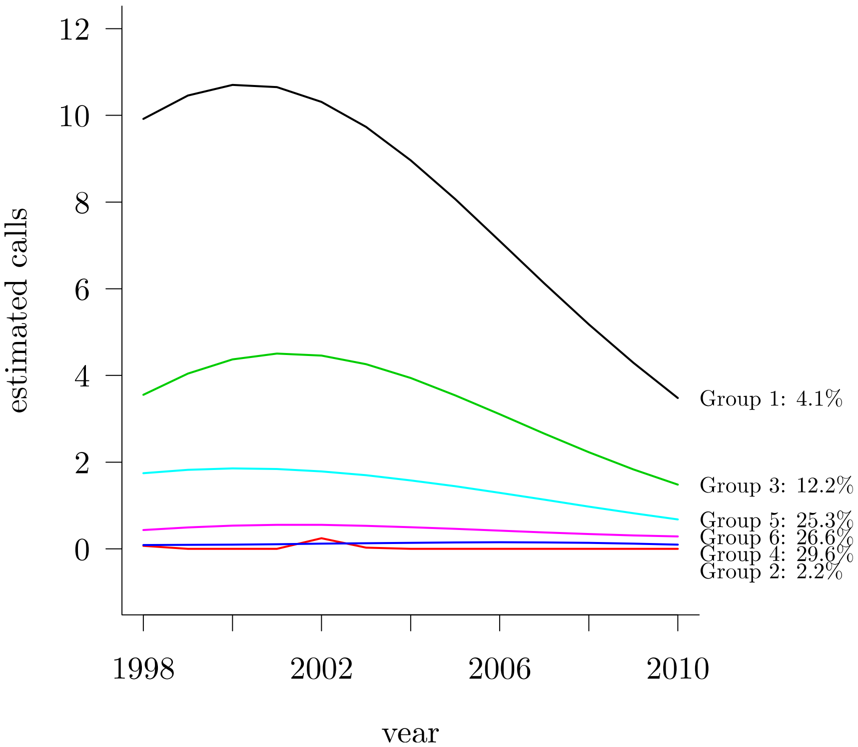


Figure 27: Group trajectories across South East Queensland (suspicious fires)

The pattern of the groups seems to be generally monotonically decreasing, at least for the groups that displayed suspicious fires at the start of the time window. It is difficult to distinguish the individual trajectories of each group particularly those with a low frequency of calls per year. In order to examine these in greater detail, Figure 28 shows the observed longitudinal pattern of suspicious fires alongside the estimated trajectory for the individual groups (indicated by the solid line). Note the limits of the y axis change from plot to plot.

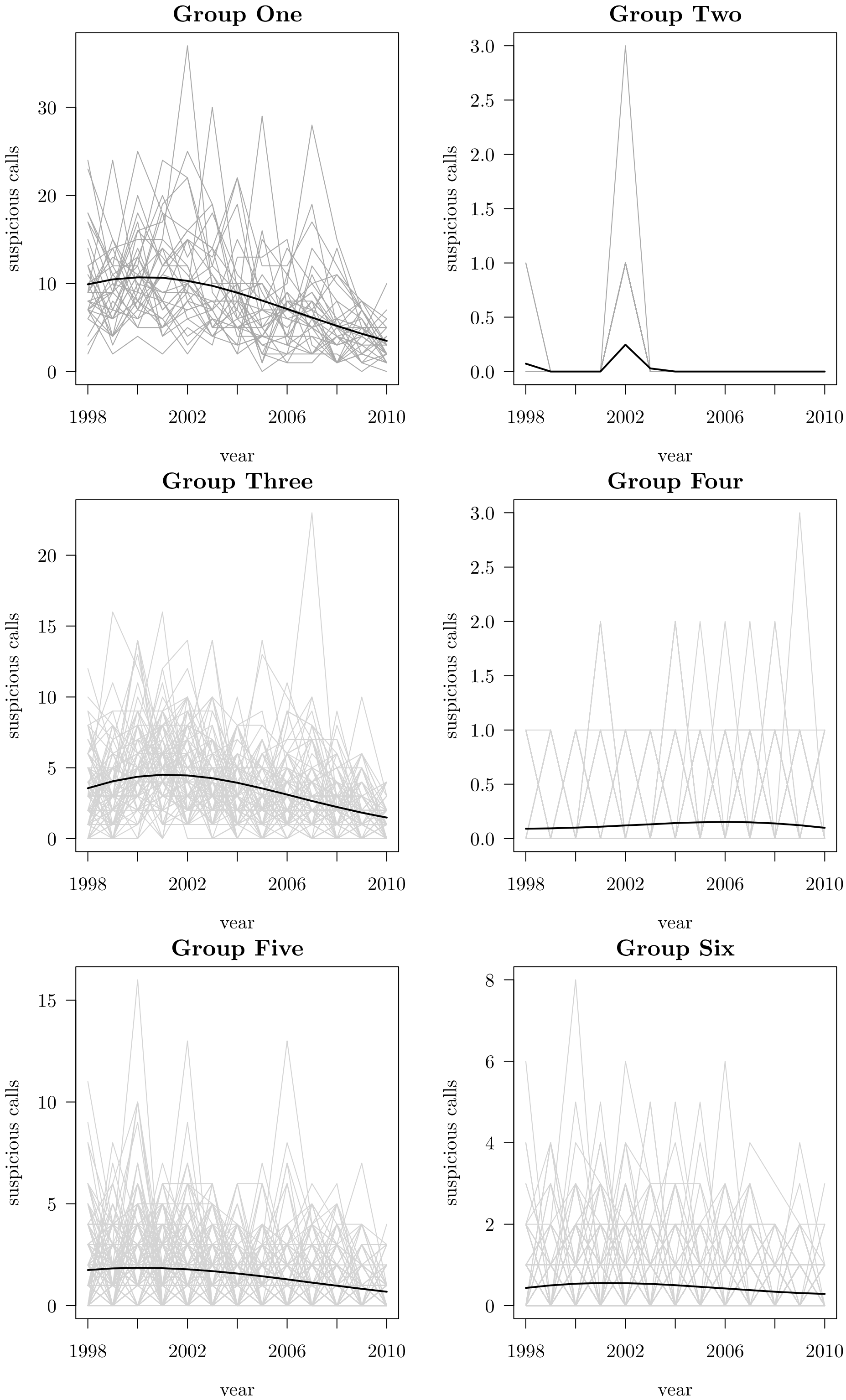


Figure 28: Suspicious fire Trajectories for All Groups (SE Qld)

Unlike hoax calls, the “zero” group for suspicious fires is not the most frequent type. Group 2 comprises about 2.2% of suburbs. Group 5 and 6 are very similar, the latter located at roughly half the volume of the former. This pattern is repeated for Groups 1 and 3. Group 4 has the highest prevalence (29.6%). Groups 4, 5 and 6 have the lowest frequencies of suspicious fires, and comprise over 81.5% of the sample.

Spatial Patterns

Figure 29 shows the low frequency suburbs (Groups 4, 5 and 6) are predominately located on the outer rim of the study region. The high rate suburbs tend to be located in the higher housing density areas of Brisbane.

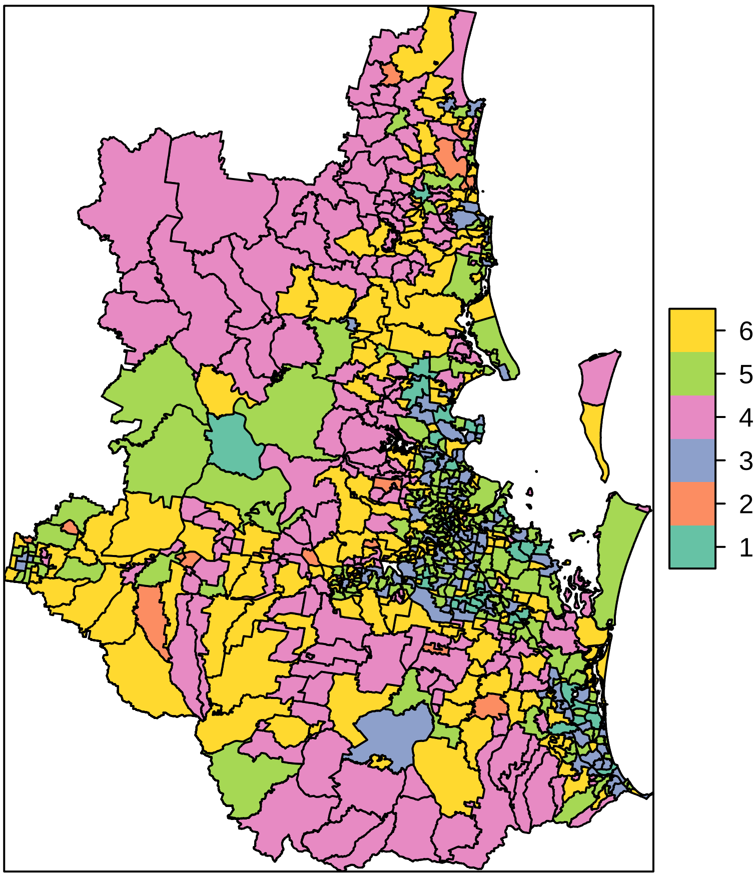


Figure 29: Group membership across the South East Queensland region (suspicious fires)

Spatial Autocorrelation

The results of the cross-K join count tests are shown in Figure 30. The *z* scores for each unique combination of group pairs are shown, with vertical lines representing the p-value thresholds of 0.05 with a Bonferroni correction to account for the 22 comparisons being made.

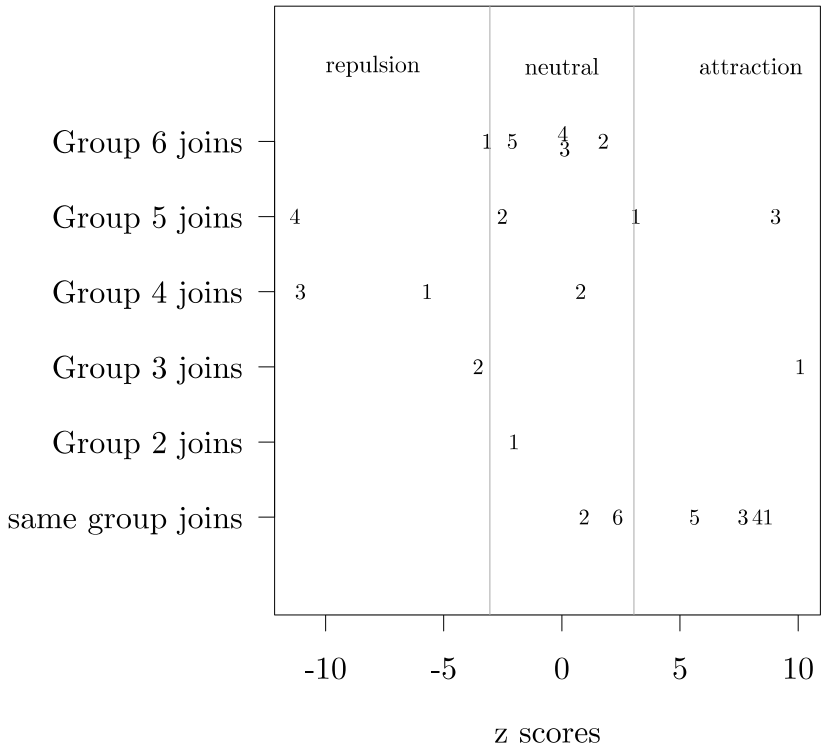


Figure 30: Results of k-group join count tests across the South East Queensland region (suspicious fires)

There is evidence that group trajectories exhibit spatial autocorrelation. The observed count of same group joins is greater than expected under the null hypothesis of random allocation for Groups 1, 3, 4 and 5. This means that groups tend to be located adjacent to each other to a greater extent than we would expect. Groups 2 and 6 displayed no significant spatial autocorrelation.

In terms of the join count results for different groups, using the repulsion, independent, attraction classification introduced by Groff, Weisburd, and Yang (2010), there are a small number that were independent (no spatial autocorrelation):

- Group 2 compared to 1, 4 and 5 separately; and
- Group 6 compared to 2, 3, 4, and 5 separately.

The following group combinations displayed repulsion (negative spatial autocorrelation):

- Group 4 compared to 1, 3 and 5 separately;
- Group 2 compared to 3; and
- Group 6 compared to 1.

The following group combinations were attraction (in addition to the same group combinations):

- all combinations of Group 1, 3 and 5.

The pattern in these results is that the suburbs with high numbers of suspicious fires tend to "hang" together, forming clusters or joins at a rate higher than expected under the null hypothesis. Suburbs with high numbers of suspicious fires are "attracted" to other suburbs with high numbers of suspicious fires and repel suburbs with low numbers of suspicious fires. Suburbs with low numbers of suspicious fires tend not to cluster together, however. The suburbs with "medium" numbers of suspicious fires tended to be located close to the low rate suburbs at roughly the expected level.

Summary

The trajectory analysis is the final component of the suite of analytic tools applied in this project and its application has extended the depth of our understanding of both malicious hoax calls and suspicious fires formed through the preceding analyses (i.e. descriptive analyses and geographically weighted regression modelling). More specifically, this technique has offered the capacity to capture *typical* trajectories over the 13 year data window for both incident types. The results reinforce the descriptive analyses and the geographically weighted regression modelling in regards to the importance of a geographically orientated approach exemplified by the prevalence of spatial autocorrelation (i.e. the tendency of observations to be influenced by nearby observations) across the majority of the group trajectories. The results from the trajectory analysis are broadly in line with the thrust of the findings of similar spatial trajectory research presented elsewhere (see for example, Groff, Weisburd, and Yang 2010). The vast majority of suburbs contain very few or no malicious hoax calls or suspicious fires with a small number hosting the bulk of both fire incident types. In terms of spatial patterns, like in similar studies, we found high volume areas that were located close to each other at a higher rate than chance for malicious hoax calls and suspicious fires. With respect to longitudinal patterns, it appears that hoax calls and suspicious fires are in decline. No areas display a long term increase in either of these incident types.

Chapter 5: Discussion and Conclusions

The two aims of this research were to:

1. To examine and capture the spatial and temporal patterning and trajectories of malicious hoax calls and suspicious fires across Queensland;
2. To ascertain the most salient socio-economic predictors of malicious hoax calls and suspicious fires; and,

In response to these aims, the research developed an integrated database describing individual level fire incident data detailing the location and timing of malicious hoax calls and suspicious fires across Queensland, the Australian Bureau of Statistics (ABS) Census data, to address five questions. The first was concerned with assessing the degree to which malicious hoax calls and suspicious fires spatially concentrated in Queensland. In response to this, the first component of the analytic strategy involved the application of a suite of spatial and descriptive methods to address this questions in which results highlighted the relatively high degree of both spatial and temporal skewness, in line with existing research in crime (see for example, Sherman, et al., 1989) and fire research (see for example, Asgary, et al., 2010). These results highlighted that there are particular locations (and places) and times that receive disproportionately high level of both malicious hoax calls and suspicious fires. For malicious hoax calls, this particularly equates to weekend days and the midnight hours with a high propensity for shopping complexes, dwellings and apartments and outdoor street locations. Regarding suspicious fires, this involves after nightfall on weekend days and especially during winter months, involving road complexes, dwellings, local and national parks and within properties with no apparent use.

The second and third questions involved assessing the extent to which spatial concentrations varied over time and seasonally in conjunction with the question of the degree to which these temporal trends can considered, persistent, transient or emergent spatial concentrations. To address these questions the *Moran temporal plot* was developed as part of this research to visually depict the changing dynamics of malicious hoax calls and suspicious fires over time to examine to what degree can these trends could be considered, *persistent*, *transient* or *emergent* spatial concentrations. This innovative technique in conjunction with a heuristic offered the capacity to categorise suburbs into one of these three types based on their spatial concentrations and its evolution over the 13 years described in the fire incident database.

The fourth question involved the application of spatial modelling techniques to understand the *key socio-economic* characteristics that explain the spatial dynamics of malicious hoax calls and suspicious fires and their variation over time. This question was addressed through the second component of the analytic strategy involved the application of a spatial modelling technique termed, Geographically Weighted Regression (GWR) to model the key socio-economic determinants of both malicious hoax calls and suspicious fires. The results highlighted the degree to which the socio-economic characteristics in the final models exhibited a great deal of spatial variation (captured through to the coefficients) in their explanation of the dependent variables (incidence of malicious hoax calls and suspicious fires). A number of independent variables were found to explain the patterning of events and these socio-economic suburb-level characteristics differed between malicious hoax calls and suspicious fires. For the malicious hoax call model these included: the proportion of people aged between 15 and 24; the proportion of one parent families; the proportion of people who had moved the house in the last five years; the proportion of people who were born in a non-English speaking country; and the proportion of unoccupied dwellings. For the suspicious fire model, independent variables included: the proportion of one parent families; the proportion of people who achieved a qualification above high school; mean household weekly income; the proportion of people who were born in a non-English speaking country; and the proportion of dwellings that are owned or being purchased. For comparative purposes OLS based models were computed using the same independent variables. For both malicious hoax calls and suspicious fires the final OLS models incorporated more independent variables (7), resulted in lower levels of explanation (lower R squared values) and possessed spatial autocorrelation issues in their residuals. In summary, it is argued that the GWR models produced better fitting models for both malicious hoax calls and suspicious fires.

The fifth and final research question involved assessing what trends of patterning could be observed over time in malicious hoax calls and suspicious fires when subject to trajectory analyses. This was addressed by the final component of the analytic strategy with the application of a trajectory analysis in which the longitudinal analysis highlighted that malicious hoax calls and suspicious fires are both generally in decline, allied by the fact that no suburbs displayed long term increases. The results identified that the overwhelming majority of suburbs across the State contained a very small number of either malicious hoax calls or suspicious fires with a highly limited number producing the majority of calls for service for both fire incident types. Common to crime related studies in which similar analysis has been conducted we found strong evidence of spatial clustering (i.e. high volumes areas that were located close to each other at a higher rate than would be expected by chance).

Significance of the research

The project is the first of its kind in Australia and internationally that has developed spatial models on disaggregated fire incident data. It has assisted in the identification of salient socio-economic and temporal characteristics that influence malicious hoax calls and suspicious fires, providing an enhanced evidence base to inform policy intervention, thereby reducing the social and economic costs associated with fires. The application of advanced spatial and statistical methods such as the local Moran visualisation and modelling, the trajectory analysis and the geographically weighted regression are applied for the first time to this dataset that has a restricted use in the public domain.

The national benefit for emergency service agencies is that the project has applied innovative methodologies through which geographical differences can be both cartographically and statistically captured and that can be used subsequently in the design and implementation of fire prevention policies. For example, knowing the places, times and salient socio-economic parameters that may bring about elevated levels of malicious hoax calls or suspicious fires can be used directly to advise strategy. This may include policy design such as a campaign to allocate a high visibility fire officer campaign into a known hotspot prior to the expected onset of malicious hoax calls or suspicious fires using the hotspot matrix framework formalised by Ratcliffe, (2004).

The results and the applied methodologies of this research will provide a foundation from which the scope of the study can be broadened to incorporate a wider range of emergency service categories.

Limitations and future directions

The research undertaken in this project represents the first of its kind in Australia to examine the spatial and temporal dynamics of malicious hoax calls and suspicious fires using a range of spatial and statistical techniques. However, while it integrates data from the fire incident database and the Census, it does not currently include other potentially influential environmental factors such as weather conditions. Future research could augment the current database structure and utilise the existing battery of spatial and statistical techniques to explore the inter-play of weather conditions on the propensity of malicious hoax calls and suspicious fires. Whereas the relationship between weather and crime has seen a long history of study (see for example, Anderson and Anderson, 1984 and Brunsdon et al., 2010) the relationship between malicious hoax calls and suspicious fires and weather remains largely unexplored from a modelling perspective. Through the integration of weather variables into the database questions including for example: *What is the interaction of these different variables – thus, for example, is the effect of a cold public holiday in a socio-economically disadvantaged area cumulative in terms of fire risk*? Developing this theme further into policy outcomes; if it were found that within the cycle of a calendar year, that there were more malicious hoax calls during school holidays in locales with particular socio-economic profiles, this could be used to directly assist in planning the allocation of finite resources during these time periods. Moreover, it would point to the necessity of further examination of the offences being committed at that time period and would suggest that crime prevention strategies aimed at school children may be appropriate.

A second area for future research is in the extension of the *Moran temporal plot* and its capacity (in conjunction with the heuristic) to classify suburbs into *persistent*, *transient* or *emergent* based upon spatial concentrations and their variation over time. The current assessment is a semi-qualitative visual assessment and whilst this has many merits associated with its relative simplicity there is the potential to augment this approach to include a quantitative assessment. This would enable a more rigorous assessment the changes of spatial concentrations over time experienced by each suburb and in doing so would advance our understanding of both malicious hoax calls and suspicious fires by more precisely classifying locales into the 3 types such that further investigations into the underlying drivers for defining the type of suburb.

Policy implications

The results from this research have provided critical information regarding the *persistent*, *transient* and *emergent* nature of hotspots of these offences which can now be used to guide optimal resource allocation in anticipation of likely load. More broadly the research has identified the general conditions under which elevated levels of risk of such fire calls exist, such that preventive strategies can be implemented. Each type of hotspot necessitates a distinct policy response. Our findings around *persistent* hotspot areas are likely to represent current agency knowledge, so we do not anticipate these findings to be novel. The Queensland Fire and Rescue Service already possess the broad knowledge concerning which areas display long-term high levels of problematic fire setting behaviour. Rather, new policy development is likely to benefit the fire service for areas identified as *transient* and *emergent*. An important research agenda beyond the scope of this project would be to link agency action and interventions to changes in problematic fire incidents. If evidence can be demonstrated that particular actions have resulted in a decline or stabilisation of problematic fire setting, this may help explain the hotspot classification. Importantly, it may very well be that areas in transition are explained by broad societal factors which have nothing to do with the fire service. Clearly this is information of equal value given that it outlines broad circumstances and contexts in which increases or decrease in problematic fire setting are triggered.

Emergent areas are a challenge to prescribe policy recommendations. By definition these are areas which have only recently displayed substantial frequency of problematic fire setting to warrant attention. It may be that, in time, these areas develop into *transient* hotspots, equally they may regress back to low-level incidents. Again, the full articulation of this is process is beyond the scope of the project, but it is likely to be addressed by considering those *transient* areas that at one point would be considered *emergent*. In other words, an early warning system could be developed that uses the longitudinal data we have developed in order to "forecast" which areas become *transient* and which decline to low incidence rates.

The researchers have been provided with exclusive access to Queensland Fire and Rescue Service administrative data and the findings from this project will be supplied back to the Service. Through improved response and prevention strategies lives can be saved and the economic burden of these types of offences can be reduced. Finally, the findings and the development of these methodological techniques have broader application to a range of other offence types.

Both malicious hoax calls and suspicious fires are a significant burden to the community, financially and in the potential danger they cause. The findings discussed herewith have implications for targeting malicious hoax calls and suspicious fire incidents across Queensland. In particular our research highlights the need for an evidence based prevention strategy similar to Merseyside's Fire Brigade's (UK-based) fire safety campaign (see Hirschfield & Bowers, 2000) that targeted young people at schools in areas with a high incidence of malicious hoax calls. They found that "20 percent of all hoax calls were made from under 3 percent of the kiosks on Merseyside" (Hirschfield & Bowers, 2000:218). Schools located near these kiosks were, as a result, selected as distribution sites for education materials. The results from our research offers the capacity to target finite resources to similar such areas in Queensland, that if used in the appropriate manner have the capacity to save public money, safeguard property and save lives.

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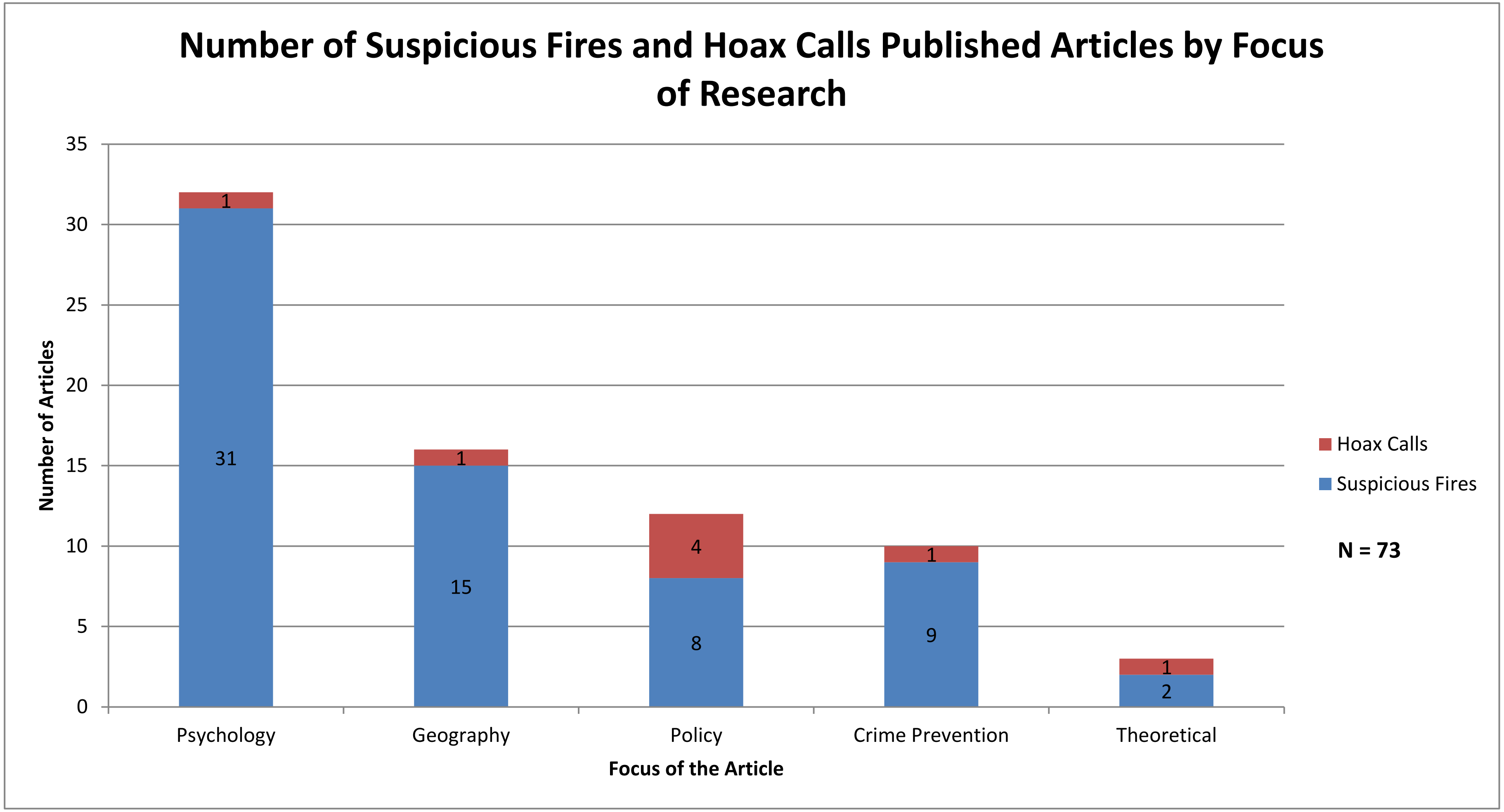
APPENDICES

Appendix 1: Number of Suspicious fires and Hoax Calls Published Articles by Focus of the Research



Appendix 2: Number of Suspicious fires and Hoax Calls Articles by Year