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The use of spatial analytical techniques to explore patterns of fire incidence: A South Wales case study

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Abstract

The application of mapping and spatial analytical techniques to explore geographical patterns of crime incidence is well established. In contrast, the analysis of operational incident data routinely collected by fire brigades has received relatively less research attention, certainly in the UK academic literature. The aim of this paper is to redress this balance through the application of spatial analytical techniques that permit an exploration of the spatial dynamics of fire incidents and their relationships with socio-economic variables. By examining patterns for different fire incident types, including household fires, vehicle fires, secondary fires and malicious false alarms in relation to 2001 Census of Population data for an area of South Wales, we demonstrate the potential of such techniques to reveal spatial patterns that may be worthy of further contextual study. Further research is needed to establish how transferable these findings are to other geographical settings and how replicable the findings are at different geographical scales. The paper concludes by drawing attention to the current gaps in knowledge in analysing trends in fire incidence and proposes an agenda to advance such research using spatial analytical techniques.

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1. Introduction

In addition to a growing literature which describes the use of Geographical Information Systems (GIS) in the emergency services, there are now dedicated conferences which explore the use of geo-spatial techniques in wider areas of emergency planning and disaster management (e.g. Van Oosterom, Zlatanova, & Fendel, 2005). In addition to the operational benefits of GIS in the fire service, in areas such as vehicle dispatch or in identifying suitable locations or boundaries for fire stations, which have been previously described (see, for example, Neely & Neal, 2002), Ormsby (2005) provided recent examples of the wider use of GIS within the fire service (for example, in terms of prevention through targeting buildings for inspection) or in examining spatial patterns of buildings at risk. Increasingly GIS is being used to visualize maps of fire safety risk assessments and to organize detailed programs of inspections or educational intervention campaigns within a forces' area. Some Fire and Rescue Services are also using GIS in fire safety checks by targeting areas or 'hotspots' of potentially high risk based on socio-economic characteristics, reinforced by analyses of previous patterns of fire incidence. In addition, GIS are increasingly being used in the preparation of Integrated Risk Management Plans (IRMP) which have been required to be drawn up by each fire service in the UK since 2004 (Office of the Deputy Prime Minister; ODPM, 2005). These plans are strategy documents that outline how each brigade will address their prevention and response objectives. Increasingly, brigades are also investigating the use of Intra-net and mobile-based GIS applications. However, as Merrall (2001) concluded, there appears to be less literature in the public domain, certainly in the UK context, that has described the use of GIS and spatial analytical techniques in analysing spatial and temporal trends in the incidence of fire risk in relation to, for example, variations in socio-economic circumstances. This contrasts with the situation in, for example, crime mapping where there have been a number of studies that have outlined the use of spatial analysis in exploring the links between such patterns and deprivation in areas such as resource targeting (e.g. Craglia, Haining, & Wiles, 2000). In general, the application of mapping and spatial analytical techniques to crime data is far more advanced in comparison to that using fire data and there are a number of texts that include such examples (see, for example, Boba, 2005; Chainey & Ratcliffe, 2005; Eck & Weisburd, 1995; Goldsmith, McGuire, Mollenkopf, & Ross, 2000; Harries, 1999; Hirschfield & Bowers, 2001; Leipnik & Albert, 2003). In addition to proprietary GIS software tools, the demand for crime mapping applications has led to the development of both stand-alone packages (e.g. CrimeStat – Levine, 2004) and extensions to standard GIS packages (e.g. the CRIMEVIEW extension to the ArcView GIS), capable of analysing spatially disaggregate crime data.

The principal aim of this paper is to examine spatial patterns in different types of fire incident call-outs using spatial analytical techniques that are more commonly applied to crime data. Specifically, the paper has two primary objectives. Firstly, we test for relationships between different types of call-outs to incidents and a variety of socio-economic variables. Previous studies have found links between social deprivation and an increased risk of fires (see ODPM (2004) for a review of those studies conducted in the previous 20 years). In this study we have used Townsend scores (Townsend, 1987), a standard deprivation index based on the 2001 Census. In addition to using the index as a whole and it's individual input variables, we further apply census variables such as housing tenure, lone parents with children under age 18, educational achievement, age (e.g. single persons aged over 65 in households), number of children, ethnicity and car ownership which have been investigated in previous studies as being potentially linked to trends in fire incidents. We examine the relationships of these variables through multiple regression approaches with different fire service call out types to examine the potential for GIS approaches to predict risk of call outs given the socio-demographic profile of an area.

The second aim of the paper is to investigate spatial relationships between different types of call outs using measures of spatial correlation or association. One of the most popular spatial techniques applied to crime data is detecting hotspots through the application of kernel density estimation (e.g. Ratcliffe, 2000; Chainey, 2002). Analysing hotspots of crime is one of the fundamental processes in understanding its spatial dynamics for a given region and in this paper we are concerned with the identification of hotspots of fire incidents for each type through the application such techniques. Such patterns could then form the basis for qualitative contextual studies in order to investigate possible reasons for such trends and we draw attention to further avenues for research in this area in the discussion.

The rest of the paper is structured as follows: in Section 2, we place our study into context by presenting the findings of previous surveys of the use of GIS in fire brigades in the UK before focusing on the use of such techniques in examining potential relationships between socio-economic patterns and fire incidence in Section 3. In Section 4, we describe the database of fire incident call-outs, and census data used in our analysis before describing the methodologies applied in the study. In Section 5, we describe the results from this analysis before providing a wider discussion of the advantages and limitations of the approach we have taken and ideas to take such research forward in Section 6. Finally we draw on the findings to provide some preliminary conclusions from this stage of our project.

2. Use of GIS in fire and rescue services

Previous surveys have illustrated an increasing use of GIS in the fire service in the last decade. There is also evidence that GIS is being used for a wider range of applications. A survey commissioned by the AGI in February 1997, that looked at the advantages and barriers/obstacles to the take-up of GIS in the emergency services in general, found that the majority of applications tended to be in emergency planning and command and control and that two-thirds of the GIS packages in operation had been purchased since 1995 (AGI, 1997). The survey also revealed generally low levels of exchange of data between the emergency services at that time and between such organisations and outside agencies. In this regard the findings mirrored those of Campbell and Masser (1995) from their survey of GIS implementations in UK local government in the early 1990s. The AGI survey also revealed priority areas for the use of GIS within the emergency services such as monitoring attendance times and hazards mapping.

Merrall (2001) conducted a national survey in 1999 of IT usage in fire brigades in community fire safety planning. This also included detailed aspects of the reporting of incidents such as the variations in the levels of geocoding (assignment of an accurate geographical reference). Seventeen of the responding 52 brigades (32.7%) did not use

GIS for fire data analysis in comparison to nineteen brigades that stated they had a GIS department. Whilst 25% of brigades used census data in their analyses, the survey also found relatively low levels of use of contextual data that could be potentially used in conjunction with fire incident data. However, at the time of the survey there were low levels of

Table 1
Summary of questionnaire results from national survey (Corcoran, 2003)

1. Background	
% of responding Brigades	54%
Average number of divisions	3
Average number of employees (civilian & fire officers)	1372
Average population coverage	1,165,478
2. Mapping brigades: mapping and software	
% Engaged in mapping	94%
Most popular mapping software	MapInfo (41%); SerWorld (31%) Other (72%)
Most popular database software	MS Access (91%); Oracle (45%) MS SQL Server (41%)
Average number of terminals dedicated to mapping	12
% involved in customisation of mapping software	62%
% integrating GPS technology	24%
2.1. Incident analysis	
Use of mapping	Command and control (69%) Incident analysis (90%) Other (38%)
Most popular type of incident analysis	Hot spot analysis (69%)
Regularity of incident analysis	Daily (17%), weekly (3%), monthly (28%), other – ad Hoc (41%)
Most popular use of incident analysis	Inform fire officers (69%) Evaluation of policies (48%) Identification for resource allocation (52%)
% involved in cross-brigade mapping	7%
2.2. Contextual data	
Most popular types of contextual data	Aerial photography (14%) CCTV coverage (14%) Land use mapping (14%)

2.3. Overall
Perceived usefulness of computerised mapping 1 (not useful)–5 (extremely useful)

1	2	3	4	5
4%	4%	27%	31%	34%

3. Non-mapping brigades: future plans	
% planning to acquire mapping software	100%
Timescale for acquisition	Within the next year (50%) 1–2 years (50%)
Planned uses for mapping	Incident Analysis (100%) Command and control (50%) Resource allocation (50%)

usage of Ordnance Survey (OS) digital data sets and skill levels within brigades in the use of mapping and GIS generally were low especially compared to the (self-assessed) skills base in statistics revealed by the survey.

A more recent survey carried out by Corcoran (2003) examined the uptake of computerised mapping across the UK Brigades and identified the types of software used, data sources and nature of geographical analysis along with the perceived usefulness of computerised mapping technologies (the principal findings from this survey are summarised in Table 1). At the time of the survey there were 58 Brigades each consisting of three divisions or territorial areas on average. Each employed on average just under 1400 fire and civilian officers typically serving a population of 1.16 million. The survey sent to each of the 58 Brigades was completed in June 2001 and had an overall response of 54%. It was found that approximately 95% of the responding Fire Brigades were using computerised mapping technologies. However, acquisition of mapping software was shown to be a relatively recent occurrence with the majority adopting mapping technologies within the previous 5 years, 24% of which acquired their computer based mapping technology since 1998 and 80% since 1996. Responding forces that were not engaged in computerised mapping at the time of the survey all intended to invest in such technology; with 50% planning to do so in the 12 months following the survey and the remainder within a 2-year period. For those Brigades engaged in computerised mapping activities, 90% had centralised all computerised mapping activities deploying a headquarters installation and some brigades had also implemented a divisional-based operation to manage mapping endeavours.

These surveys suggest therefore that there has been an increasing use of such software tools in the fire service; however, they also draw attention to wider problems of lack of co-ordination and other factors that have hindered the use of GIS techniques. The availability of detailed disaggregate sources of data since the time of the survey, particularly in relation to more accurate geo-coding of incidents, and detailed topographic data (e.g. Ordnance Survey's MasterMap™ product), however, suggests that such tools have real potential to identify spatial patterns in fire risk. In the next section, we review those studies conducted to date that have looked at such trends in relation to socio-economic patterns.

3. Socio-economic factors and fire incidence

Jennings (1999) reviewed previous research that has examined the potential association of socio-economic factors and fire incidence and risk largely from an urban (residential fires) perspective based on US studies. This was largely a review of ecological approaches in urban analysis and included a review of factors such as abandonment and property decline on intra-urban variations in fire rates and those census tract characteristics associated with fire risk. Although this review contained examples of extreme urban abandonment and dereliction in a US city context (e.g. New York) and the likely consequences for fire risk, it also highlighted the types of socio-economic factors that could be important in other (non-USA) contexts (e.g. low income neighbourhoods, household overcrowding, etc.). One of the studies reviewed by Jennings, for example, relates to a UK-based study for three urban areas in which factors such as the age of housing, housing tenure, and socio-economic status (social class, unemployment status, ethnicity) were seen to be correlated with fire rates (Chandler, Chapman, & Hallington, 1984).

In addition, there have been a number of studies that have examined the types of risk factors associated with fatal fire incidents. These have found that risks of fatalities tend to be highest in more deprived areas. Duncanson, Woodward, and Reid (2002, p. 165), for example, concluded that "fatal unintentional domestic fire incidents occurred disproportionately in dwellings in the most socio-economically deprived meshblocks." Those socio-economic factors deemed important for increased or decreased fire risk in that study are summarised in Table 2. Such studies have drawn attention to the links between certain demographic characteristics, population density and risk factors such as building types, smoking patterns, variations in smoke detector installations and levels of educational attainment; all of which have been found to correlate with such variations (Gunther, 1981; Holborn, Nolan, & Golt, 2003; Krisp, Virrantaus, & Jolma, 2005; Runyan, Bangdiwala, Linzer, Sacks, & Butts, 1992; Shai & Lupinacci, 2003). Merrall (2001) used a database detailing a 12-month log of calls for service from Greater Manchester County Fire Service for 1998–1999, in conjunction with Census derived deprivation indexes, in order to profile areas that have similar rates of fire incidence. Residential fires were shown to exhibit the strongest correlation to levels of deprivation. Malicious residential fire incidents were shown to be fourteen times higher in deprived areas compared to those classified as 'not deprived'. Merrall (2001, p. 156) concluded by suggesting that "information of this type will enable justification, monitoring, and evaluation of geographically targeted fire reduction/safety initiatives". Lapidus, McGee, Zavoski, Cromley, and Banco (1998) provided a practical example of how variations in fire incident data can be used to identify those areas of greatest need in a community smoke detector campaign (in Hartford, CT).

In geographical studies of this nature, the importance of the spatial unit of analysis has long been realised. Jennings (1999) cited the work of Karter and Donner for five cities in the States who found that the strength of the relationships between population and housing characteristics and variations in fire rates were dependent on whether census tracts or census blocks were used as the spatial unit of analysis. In the UK context, Holborn et al. (2003) showed how the spatial unit of investigation is an important consideration in such studies by looking at the relationship between deprivation and death rates from unintentional fires at the levels of London Boroughs and electoral wards. In both cases however the unintentional dwelling death rate increased with increasing social deprivation.

In addition, a number of studies have focused on the demand for services. Coombes and Charlton (1994) in an early study of fire data in South Yorkshire, for example, explored the effect of population distribution on the demand for fire services and ultimately the costs of providing such services. Using a GIS-based approach they assessed whether the current distribution of fire stations was sufficient to provide adequate cover. Adequate cover is defined through a measurement of time and distance from a point to its nearest fire station. If all computed values are less than the maximum permitted value

Table 2
Socio-economic factors associated with increased or decreased fire risk (after Duncanson et al., 2002)

Negative correlation (decreased fire risk)	Positive correlation (increased fire risk)
Home ownership (% housing units owner-occupied)	Under-education (% of persons aged over 25 with less than 8 years schooling)
Adequate income (% households income over $15,000)	Housing crowdedness (% of households with more than one person per room)
Parental presence (% of children under age 18 living with two parents)	Poverty (% of persons below the poverty level)
Good education (% of persons aged over 25 with at least high school education)	

(determined by the UK Home Office), then the cover is deemed 'adequate'. If fire cover was found to be insufficient, then another fire station is added to the region, the siting of which attempts to improve the overall adequacy of the fire cover. They conclude by suggesting that the use of this GIS-based approach provides strong support for the effect of population distribution on fire service provision and costs.

Finally, GIS have also been used in visualising spatial and temporal patterns in incidence; Dodge (1996), for example, used GIS-based techniques to explore the spatial and temporal dynamics of fire incident data. Using 12 months of calls for service data from the South Wales Fire and Rescue Service (formerly known as South Glamorgan Fire and Rescue Service), Dodge identified that the weekly distribution of fire incidents is non-uniform with small fires and malicious false alarms tending to occur on Fridays and Saturdays and false alarms (good intent, i.e. non-malicious) being more common during weekdays. Using Townsend deprivation scores, the association of socio-economic patterns and types of fire incidence were explored in order to examine the associations of patterns of malicious false alarms and major fires to that of deprivation. In addition map animation was used to show the spatio-temporal dynamics of fire incidents. Krisp et al. (2005) also looked at the use of GIS-based visualisation techniques in an exploratory analysis of fire risk in Helsinki, Finland in particular in examining relationships between population density and incident density. In our future work we plan to extend data mining and visualisation techniques building on such research; however in this paper, we are primarily concerned with a preliminary spatial analysis of fire incidence using relatively well developed and documented techniques that have been widely applied in other contexts such as crime and health applications.

4. Methodology

4.1. The approach taken

Jennings (1999, p. 27) concluded from his review that ecological approaches ''provide a valuable framework for discussing and enumerating the factors contributing to the fire problem. This approach has been applied with considerable precedent and offers great promise for understanding more fully the socio-economic determinants of the fire problem.'' In this study, we have explored the relationships between socio-economic variables in a wider geographic context to take in fire call-outs in a variety of urban and rural settings which also includes some of the most deprived (and most affluent) census areas in Wales. In particular, the study area covers some of the most deprived areas in the UK (e.g. former mining areas with significant social, health and economic problems) contrasting with some of the most affluent communities (such as those of the Vale of Glamorgan) and provides a good ''test-bed'' for the use of such techniques in contrasting social circumstances. During the course of the investigation we have had access to a disaggregated database of different calls for service over a four-year period and have explored the use of spatial analytical techniques in analysing this rich source of data.

4.2. Detailed description of the database

The disaggregate data used in this study comprises fire brigade call-outs spanning a 4-year time period (1st January 2000–31st December 2004) including incidents of primary fires involving property (FDR1), vehicle fires (FDR1V), secondary fires (FDR3) and false alarms with malicious intent (FAM); see Table 3 for further details on incident types. It is recognised that the current classification of incident types is relatively broad, especially so for the case of secondary fires, with potential implications for the interpretation of causal factors. However, due to nature of the available data provided it was not possible to disaggregate into finer categories. This is a potential avenue for further research.

Data have been made available for the South Wales Fire and Rescue Service command area which covers a population of just under 1.4 million (based on 2001 Census of Population figures). The comand area consists of 1 division and 50 individual fire stations covering approximately 2,810 square kilometres and including the major urban centres of Cardiff, Merthyr Tydfil, Newport, Pontypridd, Monmouth and Barry as well as more rural and valley communities of South Wales (Fig. 1).

For each call-out, a date, time, grid reference and incident type has been supplied. In all, data were collected for 13,286 FDR1s, 16,872 FDR1Vs, 62,895 FDR3s, 6112 FAMs, (99,165 incidents in total). Although improvements in the accuracy of the geo-referencing have been made since 2002 in the South Wales Fire and Rescue Service area with the introduction of hand-held Global Positioning Systems (GPS) with readings taken at the actual location of incidents, for a variety of reasons the location of some incidences are approximate. These include the case of non-addressable locations including, for example, stretches of motorway where incidents are often tagged with the location of the nearest roundabout. In addition, although all incidents from 1999 onwards have been given a spatial reference, from 1999 to 2002 grid references were drawn from a gazetteer with only about 30,000 location records. Many incidents were tagged with "parish references" which were a single location within a fire service defined local area. Thus for this time period in our study there is the possibility that we have identified false incident hot spots away from their actual locations. There has been an improvement in geo-coding since 2002 through the use of an improved gazetteer that now holds in excess of 600,000 records. Inevitably however there will be incidents that are incorrectly located and this could be an important caveat in the types of mapping exercises presented here.

In addition, there were 685 records that did not contain any spatial reference (0.69%), including 94 (0.7%) FDR1s, 106 (0.62%) FDR1Vs, 328 (0.52%) FDR3s, 157 (2.57%) FAMs, and were therefore omitted from the analysis described in this paper. In order to investigate any potential bias in the findings, the percentage of missing spatial references was also investigated both by year and incident type. Results from this analysis (not pre-

Table 3
Definitions of fire incident types – South Wales Fire and Rescue Service (1st January 2000–31st December 2004)

Code	Definition	Number of incidents	Percentage of total incidents
FDR1	All fires involving property, e.g. dwellings, public buildings, workplaces, etc.	13,286	13.40
FDR1V	Vehicles	16,872	17.01
FDR3	Derelict buildings/vehicles Refuse/refuse containers Outdoor structures, e.g. fence, gate, road sign, etc. Grass	62,895	63.43
FAM	False alarm deemed malicious/deliberate	6112	6.16

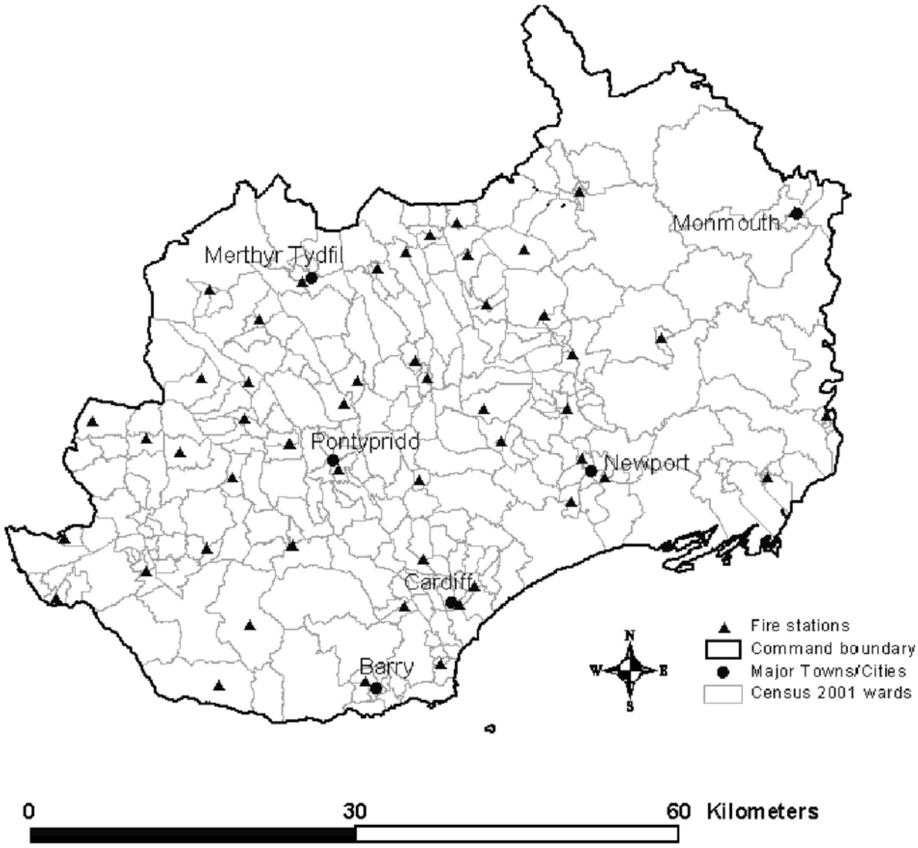

Fig. 1. South Wales Fire and Rescue Service command area.

sented here) indicated that for each incident type, those missing a spatial reference have become progressively fewer in more recent years. The largest difference, for example, was for the FAM incident type; for the year 2000, for example, missing spatial references totalled 7.7% which improved to 0% in 2004. This was therefore deemed not to significantly influence the results presented in this paper. In addition, incidents occurring beyond the confines of the South Wales Fire and Rescue Service command area were also removed from any analysis as these incidents did not represent typical activities, therefore analysis of these incidents against, for example, that of the population of the area would misrepresent their influence.

The underreporting of incidents to the fire and rescue service is an issue that researchers studying trends in fire data need to be made aware of in terms of the potential number of unreported/undetected incidents that occur. This phenomenon is well documented in the study of police data, termed the "dark figure" of crime (Coleman & Moynihan, 1996) and where attempts have been made to estimate levels of underreporting in the Home Office's British Crime Survey. A component of the Survey of English Housing (SEH) (ODPM, 2006) (a large household survey administered annually) is designed to extract additional information on domestic fires that is supplementary to that reported by fire and rescue services. In 2004/2005 the SEH estimates a total of 308,000 households to have experienced one domestic fire, a figure considerably higher that reported by fire and rescue services. SEH reported that the fire and rescue service were called to attend only 22% of domestic fires. For fires that started outside the house this figure was 71%, compared to only 15% for fires starting indoors. Fires that were started deliberately resulted in a 71% attendance by fire and rescue services. No information for either vehicle or malicious calls is reported in the SEH survey. Despite the indication that fire and rescue services appear to have a relatively large underreporting component, the incident data recorded by command and control systems still remains the most complete record of fires and the demand on fire and rescue services. However, it should be recognised that this is neither a complete record of all fires and that its completeness varies by incident type.

Using the location of incidents we have aggregated the total number per ward of similar incidents of the specific types shown in Table 3 using a GIS and calculated rates of incidence per 1000 population using the population of the ward resident at the time of the 2001 Census of Population. For each incident type used in the study there is a highly significant correlation ($p < 0.01$) between the count of population and number of fires. The problems of using this as a denominator are considered later; however, this does have the advantage that the Census was conducted within the time period for which we have incident data. The selection of Census data variables to be included in the modelling exercise was partly guided by previous literature/studies alluded to in section three of the paper.

4.3. Spatial techniques

Firstly, a spatial investigation of each incident type was conducted comprising the production of both incident rate maps for wards and kernel density 'risk surfaces'. The ward analysis (Fig. 2) classified by the rate per 1000 population identifies the relative populations at risk, whilst the kernel density surfaces (Fig. 3) permits an investigation of the spatial concentration of incidents that is unconstrained by administrative boundaries. The density of incidents for each type modelled used Kernel Density Estimation (KDE) (Silverman, 1986) was used to produce 'risk surfaces' for each incident type. In many cases the volume of mapped incidents created visualisation problems at the point level, where multiple incident localities appeared as a single occurrence (each point was simply positioned one above another thus appeared incorrectly as a single incident). This phenomenon can be due to the scale at which the map is being viewed and/or because grid references of incidents are often estimated to the nearest 100 m. KDE was used to provide an indication of incident concentration across the study region, whilst not being constrained to a boundary as is the case with aggregate mapping. KDE has thus become a popular visualisation method where the volume of incidents are relatively large and spatially clustered (Brunsdon, Corcoran, & Higgs, 2007; Chainey, 2002; Ratcliffe, 2000). The 'risk surface' output of the KDE (Fig. 3) distinguishes between areas of high concentration of fire incidents (indicated by darker shading) and lower concentrations (indicated by light or no shading). The KDE approach works by passing a kernel of a given size (bandwidth) across the study area generating counts of the number of fires (of a given type) that fall within the area of the kernel. Therefore the physical area of the kernel becomes the denominator and the number of fires counted in each kernel, the numerator. It is recognised that for most studies of risk that the denominator is typically measuring the *at-risk* population rather than the physical area as used here. To calculate a measure of the *at-risk* population for property fires could be feasible using detailed Ordnance Survey data (i.e. a geocoded

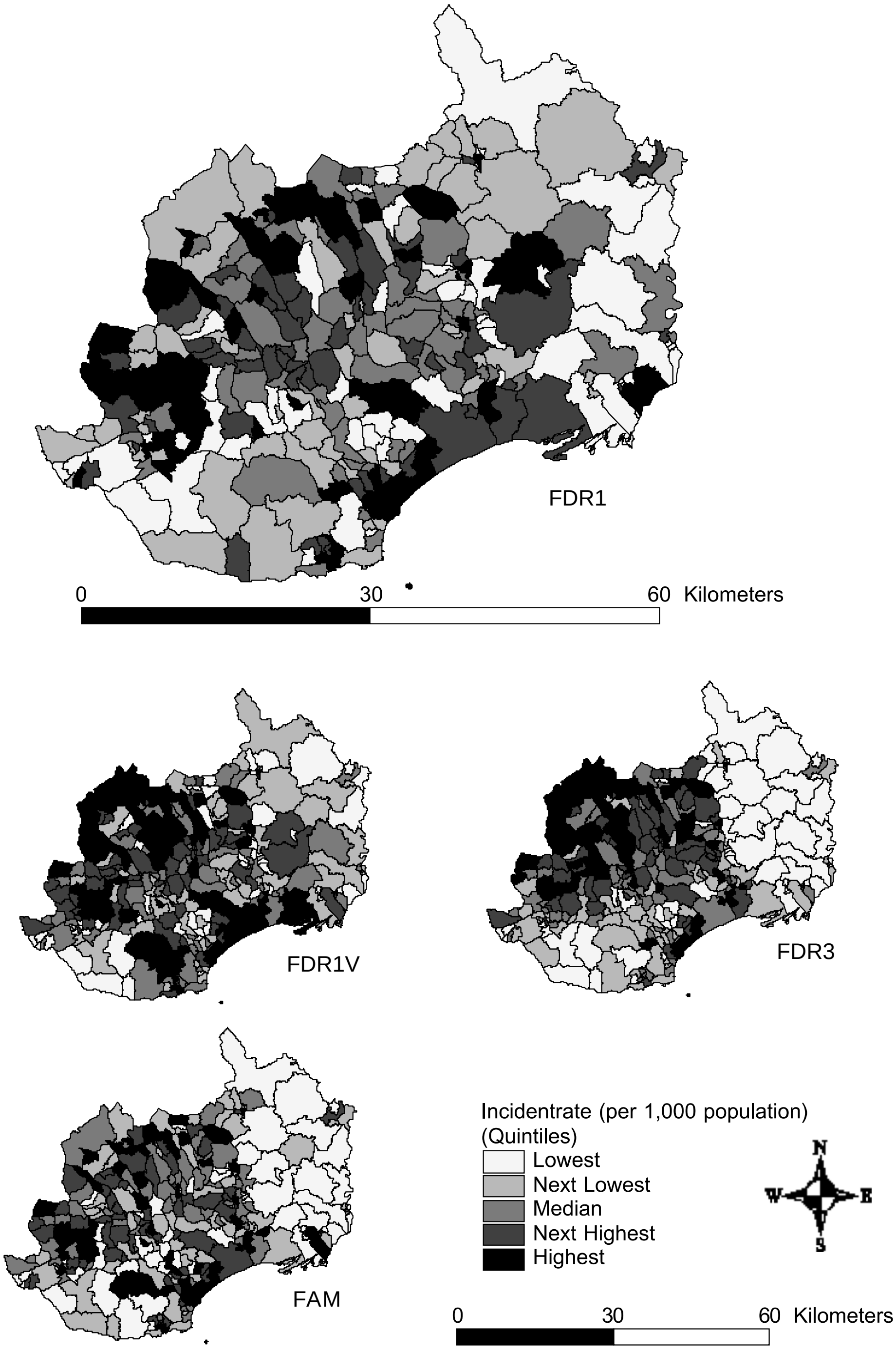

Fig. 2. Incident rates for wards.

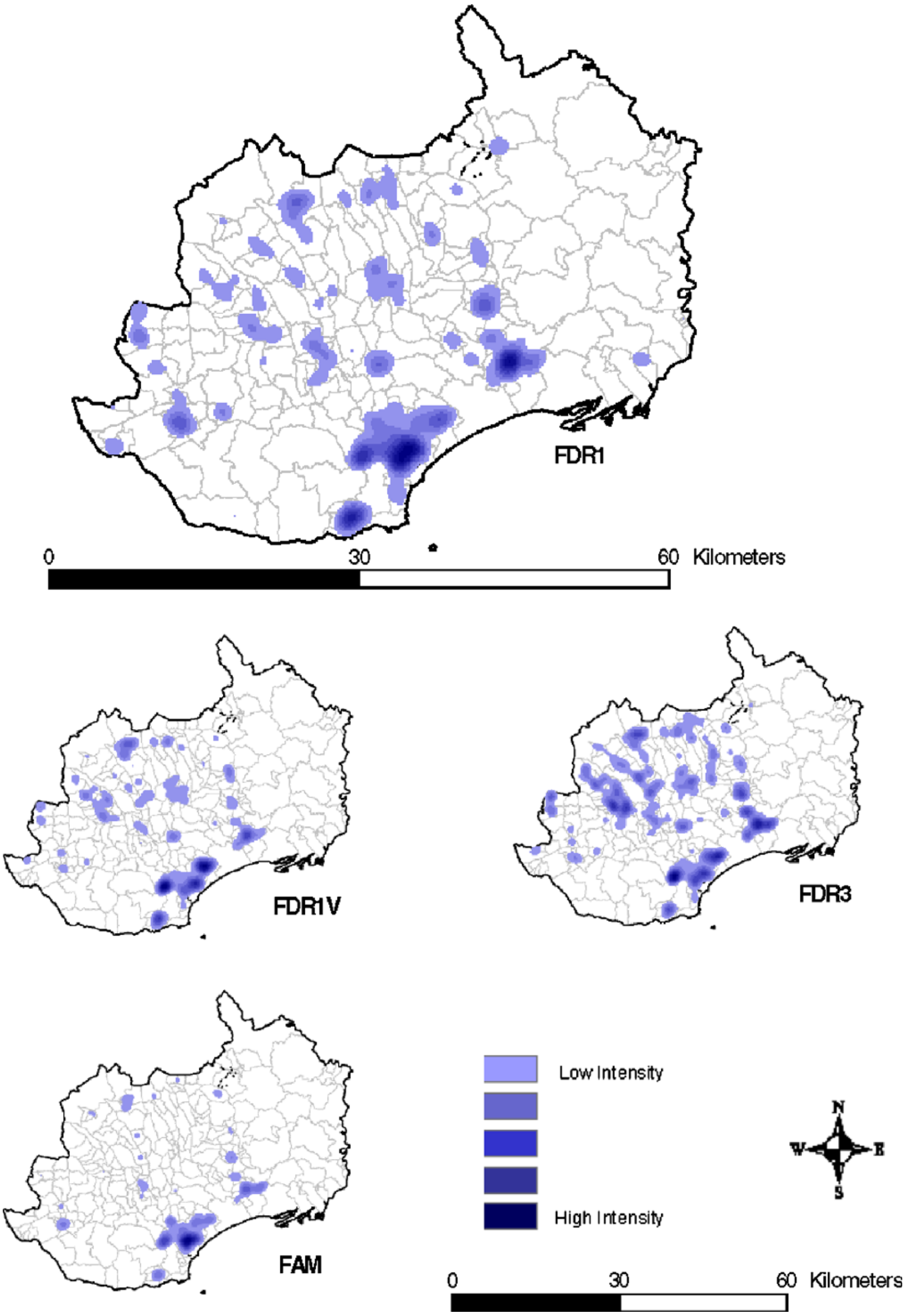

Fig. 3. KDE surfaces for each fire incident type.

gazetteer of all properties in our study area); however to generate the equivalent for vehicle, secondary fires and malicious calls poses significant difficulties. It was therefore decided to use physical area as the denominator in this preliminary study and recognise the development of measures of *at-risk* populations as a focus for ongoing research. The grid size used in the KDE analysis in this study was set at 250 m.

The most influential parameter (on the resulting output risk surface) is the choice of bandwidth. The bandwidth parameter controls the smoothness of the density estimate. Very low bandwidth values will yield 'spiky' density estimates where each spike is associated with an individual data point (i.e. a single fire incident), whilst high bandwidth values produce smoother density estimates. The selection of an optimum bandwidth has been the focus for a number of quantitative studies (see, for example, Bowman, 1984; Bowman & Azzalini, 1997; Silverman, 1986). A simple yet effective method is that of 'trial and error' whereby the user produces a number of KDE surfaces using a range of different bandwidths. An acceptable bandwidth is one where the resulting output is neither too 'spiky' nor too smoothed – using this approach, and after experimentation, a bandwidth value of 2 km was selected and the resulting outputs discussed in Section 5.1.

4.4. Statistical techniques

4.4.1. Pre-processing of data

The initial set of data consists of some 32 predictor variables, some of which show a great deal of correlation. Unfortunately, high degrees of co-linearity in predictor variables can lead to problems of coefficient estimation. This finding concurs with that of Gunther (1981) in his study of factors influencing causes of fire in Toledo, OH in that race and income were intrinsically related together as well as with other census variables such as education and home ownership. This tends to lead to situations in which arbitrary linear combinations of some of the explanatory variable coefficients perform almost identically in terms of y-variable prediction. Thus, although models in which explanatory variables are correlated may perform well in terms of prediction, they are less successful in explaining processes, as there can be a great deal of variability in the coefficient estimates. There are a number of techniques designed to overcome this problem, such as ridge regression, LASSO regression, or partial least squares regression (Hoerl & Kennard, 1970; Tibshirani, 1996; Wold, 1966). Here we adopt a simpler technique which is designed to reduce the co-linearity problem whilst maintaining reasonable ease in interpreting the analysis. A further advantage of this approach is that it may be naturally applied to Poisson regression (or negative binomial regression). The method is outlined below.

The approach taken in this paper is to divide the 32 explanatory variables into a number of natural groups, according to their subject matter. This gives seven groups, pertaining to car ownership, educational attainment, ethnicity, household structure, family structure, age profile and housing tenure (Table 4). For each group, a principal components analysis is carried out, and the first principal component is noted. Since each of the variables are percentages based on aggregation to census ward level, one would expect a degree of correlation to exist between groups – for example, an increase in the percentage of two car households must inevitably be accompanied by an overall reduction in the percentages in other categories of cars per household. Taking a single principal component from each group is intended to overcome the between group correlation approach. To help interpret each component, the loadings are listed in Table 4. For each group, only the

Table 4
Results of initial principal components analysis

Variable group name	Variable name	Loading
cars – *Lower Car Ownership Rates*	car_1	0.256
	car_2	−0.935
	car_3	−0.230
educ – *Higher educational attainment*	educ_1	−0.186
	educ_2	0.121
	educ_3	0.200
	educ_4_5	0.954
ethnic – *White population*	mixed	−0.258
	asian	−0.919
	black	−0.283
family – *Childless couples*	marr_nochild	0.766
	Loneparent	−0.265
	Oneperhh	−0.570
housing: *High Owner Occupation*	owner_occ	0.764
	Council	−0.640
people: *Low elderly and long-term illness*	llti	−0.870
	over65	−0.428
hholds: *Lower crowding*	lt1.5ppr	0.987
	Gt1.5ppr	0.160

component loadings of notable size are listed, and an attempt to name the component is supplied. This will be useful when interpreting the regression coefficients.

4.4.2. Regression techniques

Since the demand variables in our present study are based on counts, we have assumed that the probability distribution of the dependent variable is a non-negative integer such as the Poisson or negative binomial distribution (for a more detailed discussion on the techniques presented in this section and their application to geographical data, see Bailey & Gatrell, 1995, pp. 299–312). The Poisson distribution is appropriate if the occurrence of incidents has a 'lack-of-memory' property – that is the chance of an incident occurring in any area does not depend on when an incident previously occurred in that area. This is equivalent to assuming that individual events are independent of each other. On the other hand, the negative binomial distribution models a situation where events occur in clusters, so that if one event occurs, several connected events could follow. Thus for a given mean number of incidents in a time period, one would expect a greater variance for the negative binomial distribution, since the 'clustering' characteristic suggests that either very few incidents would occur, or very many. There are a number of approaches which allow regression models assuming either Poisson or negative binomial distributions for the dependent variable to be calibrated. There are also techniques which allow the two models to be compared, allowing one to infer which of the two is the most appropriate. These are generally based on the fact that for a Poisson distribution with mean k, the variance is also k. However, the negative binomial distribution has an additional parameter h which specifies the degree of clustering. For this distribution, the variance is $k(1 + hk)$ so that when $h = 0$ we have a Poisson distribution and when $h > 0$ there is extra-Poisson variation, as one would expect for clustered data. Thus, a key test for clustering is to test the null hypothesis that $h = 0$ – or alternatively inspect the model estimate for h and its standard error or confidence intervals. It should perhaps be pointed out that this essentially checks for clustering at within-ward level, rather than correlation between the wards, since although a negative binomial distribution assumes casewise clustering for the counts of incidence in each ward, it also assumes that each ward's count is independent of the other wards. At a future date, it may be valuable to examine data models allowing for inter-ward correlation. However, given the scale of the 'at risk' targets, it seems reasonable at least for a preliminary exploration, to model (and test for) clustering at the within-ward scale.

5. Results

In this paper we have been primarily concerned with an exploratory analysis of variations of fire incidence in relation to socio-economic data in the study area and with any concentrations of incidents as revealed by spatial statistical techniques. Therefore in this section we do not intend to focus on a particular ward or set of wards which have greater or lower levels of different types of fire in this paper (although clearly this would be important for the Service in strategic planning). Rather we are firstly interested in overall patterns in relation to the types of variables noted as significant in previous studies and secondly with any spatial clustering of incidence for differing types of call-outs (for example, how do the patterns of hoax calls compare to that of other types?). These in turn may help with regard to the targeting of safety or prevention initiatives within the Service.

5.1. Spatial analysis

Findings from the spatial analysis of the database can be divided into two main strands; the first explores the spatial distribution of each incident type using Census wards and KDE surfaces, and the second investigates the association of incident types to socio-economic variables using the Townsend index of multiple deprivation (Townsend, 1987). Townsend scores are constructed from small area census data on unemployment, non-home ownership, non-car ownership and household overcrowding (>1 persons per room). We have calculated such scores for all wards in the study area using data derived from the 2001 Census. We use Townsend scores for consistency with previous work (Dodge, 1996) and so that our approach can be consistently replicated elsewhere in the UK. The official government Index of Multiple Deprivation (IMD) could have been used, but since different schemes have been developed by country, results here for Wales would not be comparable with others which may be obtained in England, Scotland or Northern Ireland. Results at this stage from the ward level analysis (Fig. 2) and that from creating KDE surfaces (Fig. 3) highlight three key trends that may warrant further study:

- Firstly, less deprived wards (based on Townsend score) located towards the east of the command region near Monmouth and in the south west (west of Barry), tend to be associated with the 'lower risk' categories for each of the incident types.
- Secondly, both FDR1V and FDR3 fires have a concentration of *high risk* wards located in the north of the command region (towards Merthyr Tydfil). FDR1V fires

additionally have *high risk* wards located in the south around Barry, Cardiff and Newport. The KDE surfaces show that whilst there is a higher risk of fire towards the north, the higher spatial concentrations of these incidents tend to be located in the south (particularly in the case of FDR1V).

- Thirdly, all incident types exhibit a common high spatial concentration in the south of the command region – a consequence of a higher concentration of population in such areas.

The second element of the spatial analysis has been to explore the relationship between each of the incident types and the Townsend index of multiple deprivation. Fig. 4 shows the distribution of the Townsend score across the command region, where the more affluent wards are generally located to the east and south-west; wards exhibiting greater levels of deprivation are spread across a central band in the former coal mining areas and in outer areas of some of the major conurbations. Plotting the Townsend score against the incident rate for each ward (Fig. 5) permits an initial investigation of the relationship between deprivation and incident type. Here the more negative the Townsend score the higher the level of affluence, the more positive the higher the level of deprivation experienced within that ward. Visual inspection of the scatter plots indicates a relatively strong

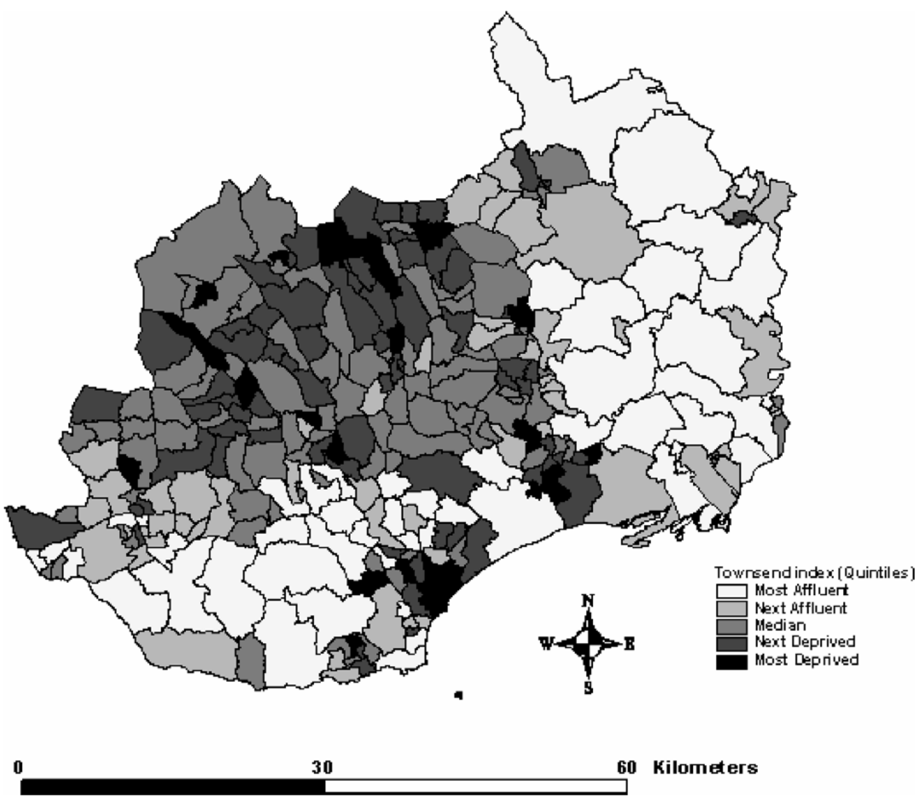

Fig. 4. Townsend index classification for South Wales Fire Service Brigade area.

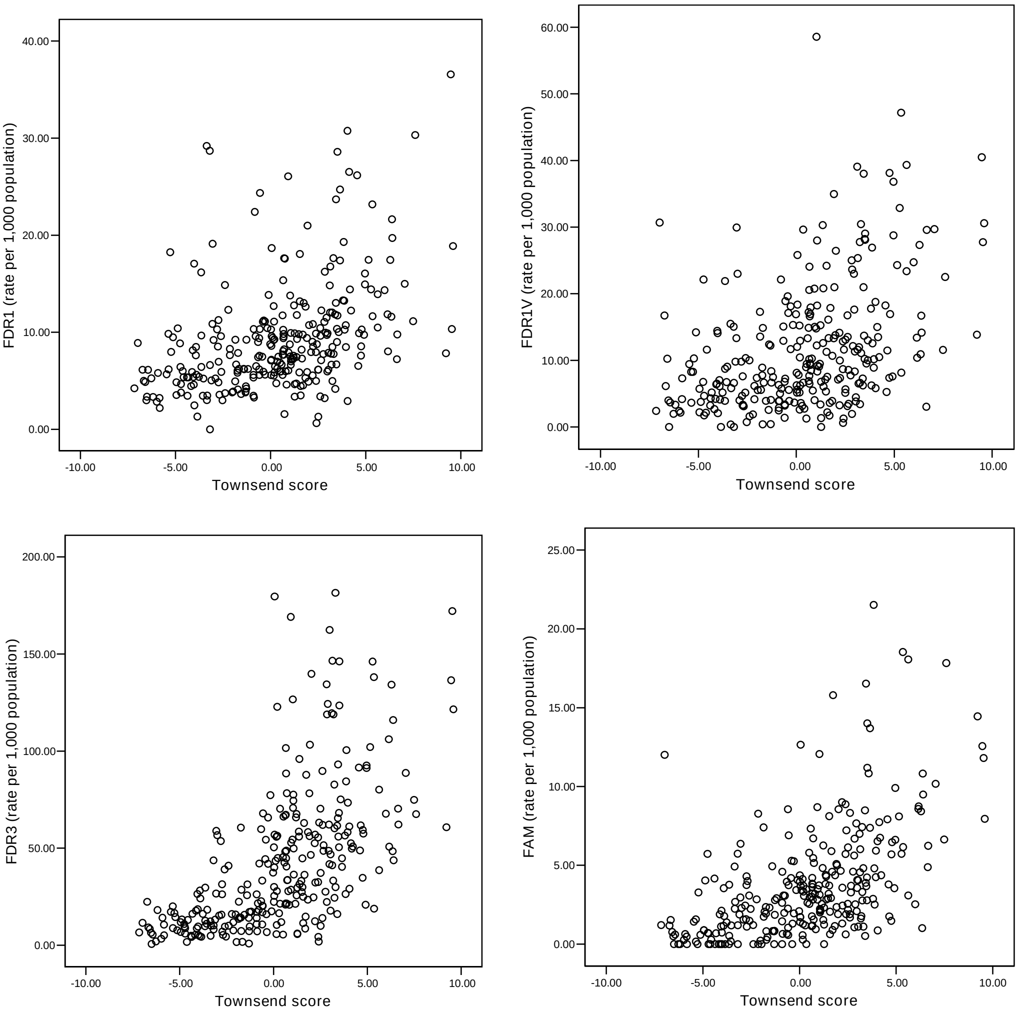

Fig. 5. Scatter plots of incident rates against Townsend scores.

positive relationship with FDR3 fires (possibly curvilinear) and that of FAM call-outs. Both FDR1 and FDR1V fires also exhibit a positive relationship; however, both are subject to a higher degree of outliers (both wards that are affluent and experiencing relatively high volumes of incidents or wards that are deprived and experiencing relatively low volumes of incidents) that may be worthy of further investigation.

The analysis of fire incidence call-outs in relation to spatial patterns in deprivation indicators such as the Townsend measure are useful in developing an initial understanding of associations between incidents and deprivation. However, such compound measures might act as to 'straightjacket' the analysis since high and low values of the separate input variables may cancel out in any one ward and thereby affect our ability to fully capture the associations. To address this point we now investigate the relationship between incident type and deprivation using 'unconstrained' Census variables.

5.2. Regression results

The regression model was fitted for four of the call-out variables – FDR1s, FDR1Vs, FDR3s and FAMs. For each variable, both a Poisson and a negative binomial error model were fitted. Recall that the negative binomial model allows for greater variance in predicted counts than the Poisson model, since it allows for a degree of clustering of events. The results for both kinds of model are tabulated in Tables 5a and 5b.

A key observation here is that the estimates and standard errors for the h parameters in each of the negative binomial models suggest that for each dependent variable some degree of clustering is evident. This effect is most marked for household fire incidents, but is of note in all kinds of incidents. In both Poisson and negative binomial models, coefficients nearly always have the same sign, and in some cases, the estimate of the coefficients are extremely similar. The only cases where signs differ are ones in which the coefficient is not significantly different from zero in the negative binomial model. The Poisson model suggests that nearly all of the coefficients in all of the models are significantly different from zero. However this should be treated with caution. The Poisson model's assumption of non-clustering leads to an estimated variance for the response variable that is lower than expected when in reality clustering does occur. This in turn leads to underestimation of standard errors for the coefficient estimates, which in turn leads to inflated estimates of the *z*-scores. This implies that the probability of a false positive result in a significance test is higher than the *p*-value that would apply if the Poisson assumption of non-clustering were true. In short, the glut of highly significant results in the Poisson analysis provides further evidence that this model's assumption of no clustering is likely to be incorrect.

Given the above arguments, we will consider only the findings of the negative binomial regression, in terms of statistical significance. The analysis suggests that wards with lower

Table 5a
Results: regression coefficients from Poisson models

Group PC	FDR1	FDR1V	FDR3	FAM
hholds	0.0016	0.0769**	0.0608**	0.0188**
people	0.0074**	□0.0141**	□0.0113**	0.0404**
housing	□0.0031**	0.0022**	0.0049**	□0.0146**
cars	0.0103**	□0.0358**	0.0170**	0.0599**
family	□0.0079**	□0.0364**	□0.0101**	0.0046
ethnic	□0.0418**	□0.0049	□0.0029	0.0021
education	□0.0129**	□0.0354**	□0.0389**	0.0079**

Table 5b
Results: regression coefficients from negative binomial models

Group PC	FDR1	FDR1V	FDR3	FAM
hholds	0.00319	0.05373**	0.06507**	0.02498
people	0.00464	□0.01364	□0.00779	0.01797
housing	□0.00205	□0.00056	0.00493	□0.01478**
cars	0.00469	□0.04018**	0.02040	0.03202*
family	□0.00447	□0.02064	□0.00247	0.00496
ethnic	□0.05707**	□0.04046	□0.01235	□0.04897
education	□0.01274*	□0.04368**	□0.03434**	□0.00205
Est. of h (se)	5.2 (0.5)	2.2 (0.2)	2.4 (0.2)	2.1 (0.2)

proportions of white residents are more prone to property fire call-outs (FDR1) and that wards with lower levels of educational attainment are also more prone to FDR1 call-outs. It also suggests that wards with more crowded households are more prone to vehicle fire (FDR1V) call-outs and FDR3 call-outs. Wards with higher car ownership rates are more prone to FDR1V fire call-outs – this is perhaps trivial, and a consequence of a greater 'population at risk' where population here refers to cars and is likely to be explained simply as being due to the presence of larger numbers of cars. Additionally wards with lower educational attainment are more prone to FDR1V call-outs and FDR3 call-outs. It also suggests that wards with lower proportions of childless couples and with lower proportions of car owners are more prone to false alarm (FAM) call-outs. Broadly similar trends were found in the multivariate analysis of fire incident data and social deprivation, based on the Index of Multiple Deprivation, for 24 fire and rescue services for 2000 and 2001 (ODPM, 2004). Using the index, and the individual components of the index (such as those relating to housing, education and access to services), findings suggest that for the three Welsh fire services there was a significant relationship between the housing and education 'domains' and the number of dwelling fires. The study further found that the education domain in particular had a significant influence on the number of deliberate vehicle fires in both England and Wales but that there was also an influence of the access, housing and health domains of the composite indicator on the number of such fires. The importance of variations in the levels of educational attainment on patterns found in the present study therefore mirrors those of the findings of the wider national study reported in the ODPM (2004) report.

6. Discussion

As with any ecological study, we cannot make inferences about the relationship between fire risk and the socio-economic status of individuals. Aggregating fire call-outs to spatial units such as wards may be useful in ecological approaches in order to investigate association with census variables. However, as Rushton (1998) argues in the context of health data, by aggregating such data from the point level we are imposing arbitrary boundaries on our analysis. He suggests that there at least three reasons why data has been aggregated in health studies, namely:

- Data for such areas can easily be encoded from the information provided.
- Information is often requested for such areas – people are familiar with use of these areas.
- Recording health information for areas reduces the risk of disclosure and protects the privacy of individuals (Rushton, 1998, p. 67).

In the case of the first stage of our analysis we are able to compare the numbers of call-outs with census data that happen to be made available at aggregate scales with which policy-makers are familiar. However, Rushton questions the validity of these factors in a GIS era where we have techniques that permit an analysis of individually geo-referenced data and suggests that "a choropleth map represents a spatially filtered map using a non-overlapping, variable-size, spatial filter with filter shapes selected from available political or administrative regions" (Rushton, 1998, p. 67). In this preliminary investigation therefore we have also explored the pattern of call-outs using detailed point level data based on the location of call-outs.

In this study, in common with other studies, we have used a denominator based on the population residing and not households. Analysis (not presented here) found that that the use of numbers of households as a denominator did not have a significant impact on findings. This is because there is a strong positive correlation ($R = 0.99$, $p = 0.00$) between numbers of persons and households per ward in England and Wales. There is an urban–rural gradient with more people and households in the more urban wards (which have smaller areal extents) and fewer people and households in the physically larger more rural wards. A possible advancement, if suitable datasets are available would be to look at incidents per 1000 population working in an area. This may be a better population at risk estimate during a working day in order to remove the outliers of inner city areas in the analysis.

Clearly more research is needed to see if these findings are applicable in other (international) settings. The greatest relevance for such an audience can be derived from the application of the techniques from a policy perspective (for example, the types of spatial and statistical techniques presented here permit the identification of the populations at risk, from which the design of geographically targeted interventions to combat problems can potentially be based). Further work is now needed to apply the same analyses to other cultural and socio-economic settings in order to derive some comparison of findings. In doing this, care must be taken in the use of Census variables to ensure that their measurement criteria and that the geographical scale of analysis are comparable. This must also be observed in relation to the fire incident categories analysed and the data collection methodology that were used, for example in relation to FAM incidents, the similarity of the criteria by which the operator deems an incident to be a "false alarm with malicious intent".

A limitation of the present study, as alluded to previously, is that some incidents have a missing spatial identifier (2.57% in the case of FAM call-outs). We have not been able to fully examine the impact of these missing records both upon the spatial analysis and the regression model. One worthy exercise would be to analyse temporal variables (date and time) for those incidents missing their spatial reference in order to ascertain if there are any temporal patterns, i.e. a particular time of the day, day of the week or month of the year when a FAM is likely to be reported and see how these patterns compare to those having a spatial reference.

There are a number of potential avenues for further research using this data set that could logically follow on from this preliminary study. Firstly, including a wider range of census-based variables or a socio-demographic classification may help further explain patterns of call-outs for particular types of fire incidence. The use of such a geodemographic typology has been proposed, for example, by Brown, Hirschfield, Merrall, Bowers, and Marsden (1999) to distinguish areas of higher or lower incidence of fire incidents. There may be value in analysing trends in relation to non-census-based variables that are being made increasingly available for example through the Neighbourhood Statistics initiatives (e.g. housing benefit data or claimant counts, educational attainment, council tax bands, crime levels, etc.). There could also be a case for looking at neighbourhood type variables that explore levels of social disorganisation, population turnover or social capital and their linkages to different call-outs. This could form a useful comparison to the findings of Chandler et al. (1984) who found that stronger social networks within some communities in London and Birmingham led to lower risk of fire incidence. More work is needed to back these findings up from both theoretical and empirical perspectives.

Secondly, the database also contains the time of the call and therefore it could also be worth considering the use of more complex spatio-temporal clustering analytical techniques (such as Kulldorffs' SATscan software; Kulldorff, 2001) to see if there are either spatial or temporal concentrations and to examine if these patterns vary with types of call-outs. Detailed maps can be used to identify locations in relation to, for example, schools, bus stops and public houses. Whilst there has been some research that has used evolutionary computation technology to identify the locations of potential clusters (e.g. Yang, Gell, Dawson, & Brown, 2003, study of clusters of hoax calls), more research is needed to explore combinations of spatial and temporal clustering. This will be an ongoing area in our future research using this database.

Thirdly, this study applied regression modelling using data aggregated to wards. An extension of this work would be to re-apply the same analysis at different scales of aggregation (both larger using, for example, local authority boundaries and smaller using, for example, Output Area boundaries) in order to assess whether the current findings are scale dependent or whether they persist at either/both smaller and larger scales. Parallels between this investigation and that of others, such as Holborn et al. (2003) could then be made as to the importance of the spatial unit on the significance of Census variables used in the model and for each incident type.

A fourth avenue for further research could relate to the application of Geographically Weighted Regression (GWR) (Brunsdon, Fotheringham, & Charlton, 1996) in order to investigate whether there are spatial factors that are not captured by models applied in this paper. Malczewski and Poetz (2005), for example, apply GWR to model the relationship between residential burglary and socio-economic variables and highlight significant local variations in the relationships between risk of burglary and the average value of the dwelling and the percentage of multi-family buildings that could not be accounted for in a global multiple regression analysis. In the context of the present study, the application of GWR to each fire incident type could be used, for example, to explore the spatial variation in the relationship of risk for each of the Census demand variables and compare them to the results found here.

Spatial analytical techniques based around GIS also have the potential to help explore detailed patterns of fire incidence, for example, examining the location of such call-outs with distance from station dispatching vehicles, routing and risk analysis for each type of incident. The ODPM report (ODPM, 2004), for example, drew attention to the need for more research in the UK on variations in incidence between urban and rural areas, and the types of factors such as remoteness which may partly account for such patterns through an impact on response times. Additionally, we do not have access in this particular study to data on factors such as spatial patterns in the installation of smoke detectors that could partly explain such trends. Lapidus et al. (1998) illustrated the use of temporal characteristics of fire incidence in conjunction with other data sets (e.g. property type, origin of fire and smoke detector use) in helping to explain spatial patterns as well as guide the implementation of a smoke detector campaign.

Finally, analysis should be conducted on those fire incidents that resulted in fatalities including more detailed information about cause of fires or the characteristics of those individuals or households affected. As Jennings (1999, p. 28) noted, "limited effort has been directed at micro-level studies of fire incidents to simultaneously reveal occupant characteristics, common patterns of behaviour, and causal factors underlying losses". Research carried out for the Office of the Deputy Prime Minister (ODPM, 2004) has looked at the types of factors associated with fire-related morbidity and mortality and found that the frequency of injuries and deaths from such incidents is higher among lower socio-economic groups and that specific age groups such as children and the elderly within such groups may be at particular risk. Analysis based on hospital episode data, for example, found that those people living in the most deprived quintile of wards in England are four times more likely to suffer a fire-related injury than those living in the least deprived wards (based on the Index of Multiple Deprivation). Such trends were replicated using an analysis of incident data, injuries and deaths for 21 fire and rescue services in England and for three such services in Wales (ODPM, 2004). The release of the new Index of Multiple Deprivation for Wales in November 2005 at Lower Super-Output Area (LSOA) level offers the potential to investigate such trends in the area of our study and update these findings, though we must bear in mind that the UK's IMD schemes are country specific. The techniques adopted in this paper have the potential to permit a more detailed investigation of such patterns by highlighting areas (and times) of particular clusters of incidents.

7. Conclusions

In contrast to crime mapping, there has been relatively less research on the types of factors that influence spatial patterns of fire incidence in the UK. Possible reasons for this situation may relate to the lack of detailed geocoded data collected by fire services in the past, a comparative lower skills base in GIS within such organisations or the unavailability of such data to outside research groups. More generally, whereas spatial interventions to target areas of high crime incidence have an increasingly significant policy profile, spatial interventions to reduce the incidence of fires have remained less evident. However, GIS-based techniques have the potential to identify those household and dwelling characteristics potentially correlated with the incidence of domestic fires and thus permit maps of risk to be produced at detailed geographical scales. This study represents a preliminary attempt to investigate spatial patterns of different incident types using exploratory techniques in relation to socio-economic characteristics for one service command area in South Wales. As Jennings (1999, p. 28) concluded, "the increased use of geographic information systems offers considerable promise in bringing formerly disparate or inaccessible information together for analysis of fire-related problems". Merrall (2001, p. 167) similarly suggested that "the use of GIS and statistical analysis enhances the capacity and sophistication of the fire services information resources, enabling management decisions to be informed by quantifiable empirical evidence". Therefore studies that use such techniques to provide information on spatial variations in different fire incidents in relation to contextual data (from the 2001 Census of Population for example) would appear to be particularly timely. However, the analysis of such data sets are by no means straightforward and have involved the use of more complex regression techniques that, to our knowledge, have not been used before in such studies.

Here we have applied spatial analytical techniques to micro-level fire incident data to explore their spatial dynamics and model their relationship. This has advanced the current research through the application of such techniques to a wider range of fire incident types, which included household fire, vehicle fires, secondary fires and malicious false alarms.

Although the broad trends are similar in relation to socio-economic characteristics, derived from the 2001 Census of Population, there are some variations in the strength of the relationship between incident types which we suggest are worthy of further investigation. This type of analysis should prove useful to a Fire and Rescue Service in targeting campaigns in, for example, schools within areas where rates are higher than expected given their socio-economic characteristics, in targeting advice to households by Community Fire Safety Teams, in forecasting future spatial patterns trends in fire incidence and in analysing the potential impact of spatial interventions in any performance monitoring exercise. In our ongoing research we will be concerned with extending the type of data mining and visualisation techniques that could be used to explore such patterns in more detail.

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