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# An ecological study exploring the geospatial associations between socioeconomic deprivation and fire-related dwelling casualties in the England (2010–2019)

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ABSTRACT

Dwelling fires are attributable to the high public health burden of injury and mortality in England. The statistic shows that from 2010 to 2019, over 5,000 injuries and 200 deaths annually are caused by dwelling fires which accounts for around three-fourths of the total fire-related casualties. Therefore, it is necessary to explore the social risk factors of fire-related dwelling casualties (SCR) and identify high-risk areas in England. In this study, an ecological study design within a longitudinal framework was adopted using a spatial-temporal Bayesian regression model to determine the overall association between the Index for Multiple Deprivation (IMD) and SCR, as well as mapping the relative risk of SCR for 2019 and then predicting the trajectories and levels of sustained risk of SCRs throughout the areas in England across 2010 to 2019. The adjusted risk map shows large variability in the IMD's impacts on dwelling fire casualty risk and the significantly increased risk clustering in the North West and northern parts of the West Midland region, where the risk increases 26%–83%. The results provide an up-to-date picture and facilitate a deeper understanding of social influences on the distribution of dwelling fire risks in England.

## 1. Introduction

Dwelling fires (DF) are extremely destructive. They can lead to physical injury of a person, as well as damage to property and the environment. In the British context, the Fire and Rescue Services (FRS) have responded to 30,000 DFs every year in England from 2010 to 2019 (Home Office, 2018). Although the number of incident dwelling fires has decreased by 22 percent between 2010/11 and 2019/20 (Home Office, 2020d), the number of casualties still remains high, and the declining trend is now leveling off. Over 5,000 injuries and 200 deaths annually are caused by DFs, which accounts for around three-quarters of the total burden of fire-related casualties, and the numbers fell by 21% in the first five years and only 11% in the second in the last decade (see Fig. 1) (Home Office, 2020a; 2020b; 2020d). Among the causes of dwelling fire-related injuries and deaths, the exposure of toxic smoke or hazardous fumes accounts for 20.15% of all fatal and non-fatal casualties, followed by burns (8.50%) and other breathing difficulties (6.55%) (Home Office, 2020c).

In this study, we focus on dwelling fire casualty risk, which refers to the risk of becoming injured (non-fatal casualty) and a death (fatality) due to fires in dwellings. We paraphrase the definition given in the UK fire statistics guidelines by the Home Office that a dwelling is defined as "a property that is a place of residence, i.e., occupied by households, including residential homes, sheltered accommodation, caravans, houseboats and Houses of Multiple Occupancy (HMO)" (Home Office, 2021). This study considered all causes (accidental/deliberate) of dwelling fires, as well as causes of casualties (burns/overcome by gas or smoke and others) and severity of injuries (from first aid to hospitalized). Dwelling fire casualty risk should be differentiated from dwelling fire risk, as the former refers to "a dwelling fire event that increases the risk of injury or a fatality", while the latter refers to "the risk of a dwelling fire occurring" (Thompson et al., 2018). Although fire deaths and injuries are associated with fire occurrence, the fluctuation of DF occurrence is not in line with the change of likelihood of dying or being injured due to DFs, as shown in Fig. 2. Previous studies have also demonstrated that the increased risk of fire-related casualties is not typically just a result of a more common occurrence of fires; instead, demographic and socioeconomic characteristics that increase vulnerability are in turn significant risk factors and merit more attention and

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**Abbreviations**

| | |
|---|---|
| 95% CrI | 95% Credible Intervals |
| DF | Dwelling Fire |
| DIC | Deviance Information Criteria |
| EC | Expected Number of Casualties |
| FRS | Fire and Rescue Service |
| FSA | Fire Service Area |
| GIS | Geographic Information Systems |
| IMD | Index of Multiple Deprivation |
| LSOA | Lower Super Output Area |
| ONS | Office for National Statistics |
| RR | Relative Risk |
| E CODE | Standard National Statistics Code |
| SCR | Standardized Casualty Rate |
| VIF | Variance Inflation Factor |

further studies (Nilson et al., 2015).

Although the social dynamics of dwelling fire have been widely studied since the 1990s (Hastie & Searle, 2016; Jennings, 2013) and many risk factors have been identified by using multivariable regression (Karter & Donner, 1977) and ecological methods (Hawley, 1986), such as social structure (Hastie & Searle, 2016) and household income (Gunther, 1980), fewer studies focus on the social dynamics of DF casualty risk, whose factors have been indicated to be different from DF occurrence risk (Nilson et al., 2015; Thompson et al., 2018). A range of epidemiological studies highlighted the casualty risks are associated with educational level, income, health condition, and housing crowdedness (Bolling et al., 2003, 2004, p. 615; Nilson et al., 2015), but to date, there have been conflicts with regards to the direction of these associations (i.e., increased or decreased risk). For example, an increased casualty risk was found among households with lower education levels (Jennings, 2013; Jonsson et al., 2017; Lewis & Lear, 2003; Warda & Ballesteros, 2007), but some studies also found high-risk groups were with higher education (Nilson et al., 2015; Runefors & Nilson, 2021; Thompson et al., 2018). Income is also a contradictory factor which has been found through many studies (Baker et al., 2006; Ballard et al., 1992; Bolling et al., 2004, p. 136; Bruck et al., 2011; Diekman et al., 2008; Greene, 2012; Marshall et al., 1998). Therefore, the impacts of these social variables clearly warrant further investigation.

Geostatistics is a class of statistics used to analyze and predict the values associated with spatial or spatial-temporal phenomena, which has the potential to explore the above questions with incorporating the spatial and temporal coordinates of the data within the analyses. It has been widely used in many areas of science and engineering, including exploring the spatial pattern of dwelling fire incidence (Corcoran et al., 2013, 2007; Corcoran, Higgs, & Higginson, 2011; Corcoran, Higgs, Rohde, & Chhetri, 2011). The class of conditional autoregressive (CAR) model and its spatial-temporal extensions were commonly used to represent the spatial and temporal correlated variation in risks. It assumes the risks vary smoothly in space and time and thus account for the inherent spatial-temporal autocorrelation. A Bayesian approach to inference is typically adopted using Markov chain Monte Carlo (MCMC) simulations, which have been applied extensively in the field of epidemiology and public health (Elliot et al., 2000; Musah et al., 2019). These techniques have also been applied to explore the fire incidence risks. Previous studies found that fire incidents are not static in either time or space and that the spatial-temporal variation is related to incident type (Corcoran et al., 2007; Winberg, 2016). Considering that DF casualty risk is associated with the fire incidence, it is very likely also to exhibit some spatial-temporal patterns. However, there is a substantial paucity of studies using spatial-temporal techniques to examine both the geographical and temporal distribution of injuries and deaths due to dwelling fire (Asgary et al., 2010; Corcoran et al., 2007; Yao & Zhang, 2016).

In response, this study aims to determine the overall association between the level of deprivation in an area, as measured by the Index of Multiple Deprivation (IMD) as a proxy, and fire-related dwelling casualties, as well as mapping the relative risks of such outcomes (which is termed as Standardized Casualty Rate (SCR) meaning the probability of observing the occurrence of injuries or deaths due to dwelling fires) for the latest year (2019) in Fire Service Areas (FSA) of England, and then predicting the trajectories and levels of sustained risk of SCRs throughout the FSAs in England across 2010 to 2019. We hypothesized that the level of deprivation has a significant influence on the DF casualty risks. To verify this, an ecological study design within a longitudinal framework was developed to quantify the SCR as the outcome for DF risk in each area with consideration of the historical dataset and population. To explore the temporal trend, we traced back to 2010 when the first dataset with full categories was released since the new Incident Recording System was adopted in England (Department for Communities & Local Government, 2011), and we undertook a longitudinal approach and fitted a spatial-temporal model to explore the time trend to examine which areas have sustained high-risks of SCR from 2010 to

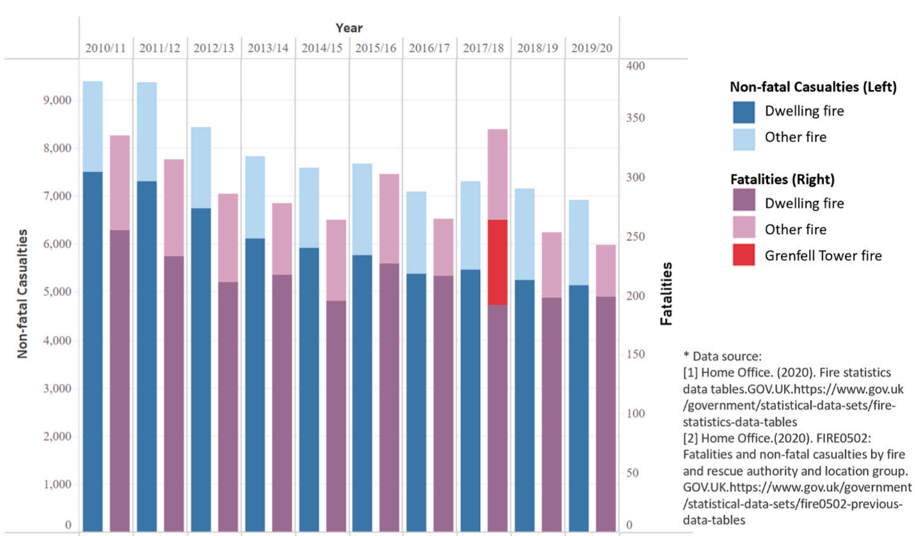


**Fig. 1.** The bar chart shows the number of fire fatality and non-fatal casualty in England from 2010 to 2019.

2019. This study focuses on the casualty risk from a public health perspective and provides fresh insights into the area by integrating statistical modeling and spatial analysis to provide contemporary findings. The results will contribute to the understanding of the relationship between key socioeconomic characteristics and DF casualty risks and support the identification of high-risk areas so as to serve as a basis for the strategic planning and allocation of resources for fire prevention, safety, and increasing awareness.

## 2. Materials and methods

### 2.1. Study area

The present study area is defined as mainland England which is delineated into 43 Fire Service Areas (FSA) (Boswarva, 2017). An FSA is a set of boundaries for the areas of operation of statutory Fire and Rescue Agencies in the UK and territories based on the Ordnance Survey Administration data, as shown in Fig. 3. Each area has its own unique FRS name and Standard National Statistics code (E code).

### 2.2. Data description

All secondary data on fire-related incidence and areal-level socioeconomic deprivation were derived from the UK's official public sector website (Home Office, 2020b). The ecologic units for each FSA have temporal data; we therefore used a longitudinal approach to explore the temporal trend and thus fitted a spatial-temporal model to predict the burden of fire-related casualties and to establish the trajectories in terms of the spatial-temporal DF risks. The data was extracted from 2010 to 2019 (inclusive). The casualty data is the sum of fatalities and injuries in each fire service area during a given year. Another variable that measures risk is population data, which measures risk per capita in different fire service areas. The population data were derived from the Small Area Population Estimates developed by the Office for National Statistics (ONS) annually, presented at the LSOA level (Office for National Statistics, 2020).

Additionally, the English Index of Multiple Deprivation (IMD, Ministry of Housing, Communities and Local Government) is selected as a covariate due to its diversity, continuity, and reliability. It is a proxy measure of socioeconomic deprivation, a regional level indicator that could be used to model the spatial-temporal variability in fire casualty risk across FSAs (Ministry of Housing & Communities & Local Government, 2011; 2015, 2019). The IMD brings together 7 domains and 39 indicators (see Appendix A), and this diversity of inputs leads to a more reliable output (Ministry of Housing & Communities & Local Government, 2019). Based on the literature review as mentioned, we chose the six most relevant domains for our study, including Income Deprivation; the Education, Skills and Training Deprivation; Health Deprivation and Disability (considering health conditions may affect people's response to fire incidence); Crime (considering deliberate included); Barriers to Housing and Services (considering SCR may be affected by house crowdedness); Living Environment Deprivation (considering SCR may be affected by house condition) and Employment domain (considering SCR may be affected by unemployment). We hypothesized that these domains were either negatively or positively correlated to DF casualty risk and used the model to assess how significant the correlations are.

The IMD scores are the original continuous measures used by the ONS to create the ranks and deciles for classifying English LSOAs from most to least deprived if they fall in the lowest decile (most deprived) or highest decile (least deprived). The ranks and deciles are published as Indices of Multiple Deprivation which, in turn, are based on scores: the larger the score, the more deprived the area (and thus the lower rank or decile it falls in) (McLennan et al., 2019, p. 117). To fit the model, we first recalculated the LSOA IMD scores to the resolution of FSA through aggregation by estimating its mean (see Appendix B for the mean and variance of each IMD). Measures for IMDs were calculated for FSAs temporally for where data are available. It should be noted that IMDs are only currently available for 2010, 2015, and 2019. Therefore, we make an explicit assumption that IMDs from the previous year will remain the same until the next interval to capture the spatial-temporal variation in fire casualty risk.

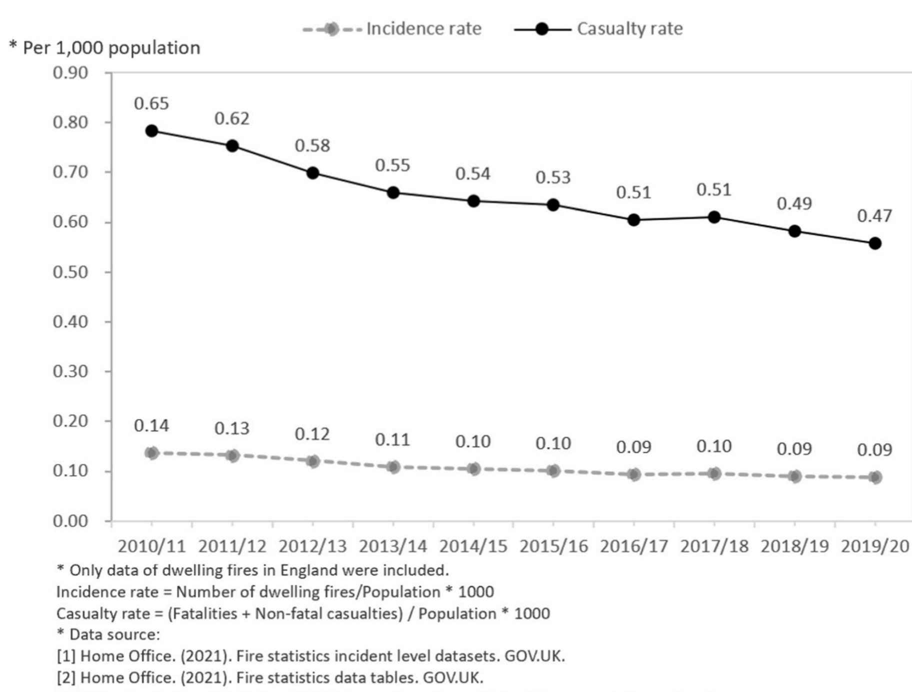


**Fig. 2.** The line chart shows the fluctuation of dwelling fire incidence rates and dwelling fire casualty rates (including both fatality and non-fatal casualty) per million population in England from 2010 to 2019.


**Fig. 3.** The geographic map of mainland England showing the Fire Service Area (FSA) boundaries.

### 2.3. Study design

This research uses an ecological study design within a longitudinal framework. All secondary data were processed and aggregated to measure the main outcome of casualty risk (i.e., the probability of death or injury due to dwelling fire) under the population size in each fire service area. By FSA ($i = 1, 2, 3, \ldots$to 43) and year ($t = 2010, 2011, 2012, \ldots$to 2019), the standardized casualty rate ($SCR_{i,t}$) is calculated by dividing the number of observed DF casualties ($N_{i,t}$) by the number of expected DF casualties under the national rate ($EC_{i,t}$) in $t$th year and $i$th FSA. As the number of casualties varies significantly with population size and year, the standardized casualty rate improves comparability over time and between areas. The implicit assumption in risk measurements is that people in areas with a higher historical casualty rate will also be more likely to die or get injured from DF in the future.

## 3. Statistical analysis

A Poisson-based spatial-temporal Bayesian regression model was used to determine the association between SCR and socioeconomic deprivation measured as IMDs as well as to map the relative risk of SCRs across FSAs in England. The R package for "CARBayesST" is an R/RStudio package for modeling the spatial-temporal data in a Bayesian framework using Markov Chain Monte Carlo (MCMC) simulation by providing a suite of models for capturing the autocorrelation via random effects that are assigned spatial-temporal extensions of conditional autoregressive (Lee et al., 2018). We used the ST.CARar function from the CARBayesST package to explore and estimate the average spatial and temporal trends of DF casualty risk while considering the deprivation levels and identifying the clusters of areal units that exhibit higher risk with a spatially autocorrelated first-order autoregressive process (Lee, 2020; Rushworth et al., 2017). Firstly, we used a series of multivariable linear regression models to test diagnostically the existence of multicollinearity among the independent variables, and taking them as a continuous outcome and then fitting it against all other remaining variables to calculate its variance inflation factor (VIF). As it can be seen in Table 1, the VIF scores for Health (VIF = 8.39), Income (VIF = 27.14), and Employment (VIF = 33.85) exceed the threshold (VIF $<4$) (Neter et al., 1996; O'brien, 2007). To overcome this problem, the three domains were removed in the following models.

After that, a series of Bayesian multivariate autoregressive models with spatially autocorrelated precision matrix was implemented to assess the effects of the four domains for IMD (i.e., those with a VIF $<4$) on the SCR of each FSA area in England over time (Lee et al., 2018). To determine the model with the best fit, we used the Deviance Information Criterion (DIC) to compare different models in which the IMD domains

**Table 1**
Using a regression model to detect the multicollinearity between IMD domains and the dwelling fire SCRs.

| Domains of Deprivation in England | VIF |
|---|---|
| Living Environment (LE) | 1.46 |
| Education, Skills & Training Deprivation (EST) | 3.23 |
| Housing & Barriers to Public Services (BHS) | 2.76 |
| Health Deprivation | 8.39 |
| Crime | 2.64 |
| Income | 27.14 |
| Employment Deprivation | 33.85 |

* The VIF score for Health Deprivation (VIF = 8.39), Income (VIF = 27.14) and Employment (VIF = 33.85) are very high (>4); thus, the three domains are removed in the multivariant regression model; they have also been removed in the univariant regression model for consistency purposes.

could be fitted accordingly with forward and backwards variable selection (Lee, 2020; McGrory & Titterington, 2007; Spiegelhalter et al., 2002; Subedi & McNicholas, 2021) and found the one fitted with all four domains to be the best since it yielded the lowest DIC of 3460.7 (Table 2). Thus, this optimum model was selected to perform any subsequent Bayesian multivariate analysis.

The mathematical formulation for modeling the relationship between the outcome (SCR) and the IMD scores covariates is given as follows:

$$Y_{i,t} \sim \text{Poisson}\left(SCR_{i,t},\ \theta_{i,t}\right), \tag{1}$$

$$\text{In}\left(\theta_{i,t}\right) = \beta_0 + \sum_{q} \beta_{q,i,t} x_{q,i,t} + \psi_{i,t}$$

$Y_{i,t}$ is the observed number of reported cases of injuries or deaths due to DFs in a given $i$th FSA and $t$th year, where $i = 1, 2, 3, \ldots$to 43 and year $t$ = 1,2, …to 10, respectively. It is assumed that $Y_{i,t}$ is from a Poisson distribution. The model parameter $\theta_{i,t}$ represents the risk of fire-related dwelling casualties when compared to the expected number of casualties $EC_{i,t}$ in a given $i$th FSA and $t$th year. The four domains for IMD are covariates represented as $x_{q,i,t}$ where $q = 1, 2, 3$, and 4. $\psi_{i,t}$ is the random effect for $i$th FSA and $t$th year. The prior specification for the coefficients of the included covariates are as follows: weak informative priors were assigned to $\beta_{q,i,t} \sim N(0, 0.000001)$. To quantify the evolution of the spatial pattern in DF risk over time, we used a spatially autocorrelated first-order autoregressive process to construct the spatial-temporal structure of $\psi_t$, whereby $\psi_t = (\psi_{1,t}, \ldots, \psi_{i,t})$ is a vector of random effects for all areal units at time t. The vector $\psi_t$ is equal to $\rho_T \psi_{t-1} + \varepsilon_t$ whereby the temporal autocorrelation is controlled by the mean function $\rho_T \psi_{t-1}$, and the covariance structure is controlled by $\varepsilon_t$, which is a vector of errors $\varepsilon_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{i,t})$ modelled as spatially autocorrelated (Rushworth et al., 2017). This $\varepsilon_t$ is given by $\text{N}(0,\ \tau^2 \mathbf{Q}(\mathbf{W}, \rho_s)^{-1})$ (Leroux et al., 2000), where $\tau^2$ is the process variance and $\mathbf{Q}(\mathbf{W}, \rho_s)$ gives the precision matrix computed by the following equation:

$$\mathbf{Q}(\mathbf{W}, \rho_S) = \rho_S[\text{diag}(\mathbf{W}1) - \mathbf{W}] + (1 - \rho_S)\mathbf{I} \tag{2}$$

where 1 is a 43 × 1 vector of ones and while **I** is the 43 × 43 identity matrix (Lee, 2020; Leroux et al., 2000). The spatial autocorrelation is induced by the neighborhood matrix **W** as defined, $(\rho_S, \rho_T)$ controls the levels of spatial and temporal autocorrelation respectively with 0 corresponding to independence and 1 corresponding to strong autocorrelation. Thus, this multivariate specification $\varepsilon_t \sim N(0,\ \tau^2 \mathbf{Q}(\mathbf{W}, \rho_s)^{-1})$ is equivalent to

$$\varepsilon_{it} \Big| \varepsilon_{-it},\ \mathbf{W} \sim N\left(\frac{\rho_S \sum_{j=1}^{43} w_{ij}\varepsilon_{jt}}{\rho_S \sum_{j=1}^{43} w_{ij} + 1 - \rho_S},\ \frac{\tau^2}{\rho_S \sum_{j=1}^{43} w_{ij} + 1 - \rho_S}\right), \tag{3}$$

$$\tau^2 \sim \text{Inverse-Gamma}(1,\ 0.01),$$

$$\rho_S, \rho_T \sim \text{Uniform}(0,\ 1)$$

where parameters $\tau^2$ was assigned an inverse-gamma prior distribution with hyperparameters defined as default values for $a = 1$ and $b = 0.01$, while $(\rho_S, \rho_T)$ was given a uniform distribution from 0 to 1. The regression coefficients are represented as $\beta_{q,i,t}$ which are reported as the relative risk (RR) ratio after being exponentiated, i.e., exp $(\beta_{q,i,t})$ with their corresponding 95% credible intervals (95% CrI). Statistical significance was deemed whenever the null value of 1 lies between the upper and lower limited of 95% CrI. We computed the exceedance probabilities by setting the threshold value as 1 (i.e., the null value for RR). Here, we are interested in determining which areas have the highest probability of having an excess DF casualty risk with RR > 1.

The above model is extensively flexible, and it was used to quantify the following: 1.) the overall univariate and multivariate relationship between each of the IMD and SCR; 2.) apply the multivariate model for the geospatial quantification of the relative SCRs and mapping such risks of SCR for the latest year 2019 across English FSAs; and 3.) finally, applying the multivariate model for the prediction of the trajectories and levels of sustained risk of SCRs throughout the areas in England across 2010 to 2019. All statistical analyses were carried in RStudio version 1.2.1335 (RStudio Team, 2020) using the CARBayesST packages (Lee et al., 2018). We ensured that all models were valid by testing convergence. For mapping and visualization, all outputs were generated using QGIS version 3.16.3 (QGIS.org, 2021).

## 4. Results

### 4.1. Univariate and multivariate association between the domain of deprivation and fire-related dwelling casualties in England

Our univariate spatial-temporal Bayesian model shows that each domain of socioeconomic deprivation in England, with exceptions of housing & barriers to public services, was positively associated with an increased risk of fire-related dwelling casualties (see Table 3). For instance, when the levels of deprivation at an FSA-level increase, we found the following for the domains: Living Environment and Education, Skills & Training, significantly increases the risk of fire-related dwelling casualties by up to 25.0% in England. For elevated levels of crime, the risk of fire-related dwelling casualties increases 13.4%. In the right panel of Table 3, the temporal dependence parameter estimates $\rho_T$ tend to be nearly as high as the maximum value of 1.0, while the spatial dependence parameter estimates $\rho_S$ are closed to 0, indicating substantial temporal correlation and spatial independence remaining in the data.

However, when we bring together the joint effects of all domains of deprivation in our multivariate model (see Table 4), we see a more modest result when compared to those from the univariate model. For instance, the increased levels of deprivation in the context of the living environment increase the risk of fire-related dwelling casualties by 24.1% after including adjustments for all other domains. Similarly, the

**Table 2**
DIC values for model selection.

| Domains included in the model | DIC |
|---|---|
| LE | 3469.3 |
| LE + EST | 3461.5 |
| LE + EST + BHS | 3462.5 |
| EST | 3471.7 |
| EST + BHS | 3471.8 |
| EST + Crime | 3474.0 |
| EST + BHS + Crime | 3475.3 |
| BHS | 3478.9 |
| BHS + LE | 3463.7 |
| BHS + LE + Crime | 3464.7 |
| Crime | 3483.7 |
| Crime + LE | 3471.6 |
| Crime + LE + EST | 3463.5 |
| LE + EST + BHS + Crime | 3460.7 |

**Table 3**
Univariate spatiotemporal Bayesian regression modelling that explores overall association for each deprivation index with fire-related SCRs and random effects.

| IMD Domain | Unadjusted Relative Risk (95% Credibility Intervals) | | | Random effects (95% Credibility Intervals) | | |
|---|---|---|---|---|---|---|
| | RR Estimates | Percentage | | $\tau^2$ [a] | $\rho_S$ [b] | $\rho_T$ [c] |
| LE | 1.248 (1.175–1.329) | +24.8% | (+17.5% to +32.9%) | 0.043 (0.034–0.057) | 0.034 (0.001–0.12) | 0.947 (0.898–0.990) |
| EST | 1.237 (1.163–1.316) | +23.7% | (+16.3% to +31.6%) | 0.044 (0.035–0.057) | 0.029 (0.001–0.110) | 0.937 (0.887–0.984) |
| BHS | 0.918 (0.863–0.975) | −8.2% | (–13.7% to −2.5%) | 0.050 (0.040–0.065) | 0.030 (0.001–0.113) | 0.924 (0.872–0.974) |
| Crime | 1.134 (1.069–1.201) | +13.4% | (+6.90% to +20.1%) | 0.051 (0.040–0.068) | 0.056 (0.005–0.160) | 0.922 (0.870–0.973) |

[a] . $\tau^2$ is the estimate of temporally varying spatial variation.
[b] . $\rho_S$ is the estimate of spatial autocorrelation (range: 0 = no spatial dependence to 1 = complete spatial dependence).
[c] . $\rho_T$ is the estimate of temporal autocorrelation (range: 0 = no temporal dependence to 1 = complete temporal dependence).

**Table 4**
Multivariate spatiotemporal Bayesian regression models that explores the overall association with deprivation indexes with dwelling fire-related SCRs and random effects.

| Domains of Deprivation in England | Adjusted Relative Risk (95% Credibility Intervals) | | |
|---|---|---|---|
| | Estimates | Percentage | |
| Living Environment | 1.241 (1.164–1.329) | +24.1% | (16.4%–32.9%) |
| Education, Skills & Training Deprivation | 1.181 (1.124–1.245) | +18.1% | (12.4%–24.5%) |
| Housing & Barriers to Public Services | 1.137 (1.094–1.184) | +13.7% | (9.4%–18.4%) |
| Crime | 1.010 (1.007–1.013) | +1.0% | (0.7%–1.3%) |
| **Random effects** | **Median (95% Credibility Intervals)** | | |
| $\tau^2$: estimate of temporally varying spatial variation | 0.035 (0.028–0.044) | | |
| $\rho_S$: estimate of spatial autocorrelation | 0.014 (0.001 to o.065) | | |
| $\rho_T$: estimate of temporal autocorrelation | 0.936 (0.885–0.986) | | |

significant increase in the risk of fire-related dwelling casualties for Education, Skills & Training, and Housing & Barriers to Public Services domains are 18.1% and 13.7%, respectively. The temporal and spatial dependence parameters are similar to those in the univariate model, which exhibits high temporal correlation and low spatial dependence. The result from the multivariate model is giving priority over those derived from the univariate model because it has the lowest DIC and accounts for the effects of multiple domains of socioeconomic deprivation at the same time (Table 2).

### *4.2. Geospatial patterns of fire-related dwelling casualty risks for England using the latest year of 2019, and sustained risk throughout 2010-19*

There is large variability in terms of the domains' impact on fire-related dwelling casualties; we can see that there is a substantial increase in the risk of fire-related casualties, as well as the risk being clustering in the Northwest and northern parts of the West Midland region (see Fig. 4). The areas in which the risks of fire-related dwelling casualties are significantly pronounced are in the Lancashire, Merseyside, Manchester, and West Yorkshire regions, with increased risks being from above 35% and close to 3-fold. In the Midland regions, the FSA that corresponds to West Midlands significantly has an increased risk of fire-related dwelling casualties above 80%. We observed isolated areas where the risks of fire-related casualties are significantly higher i.e., Tyne & Wear (RR = +32%), Humberside (RR = +22%), West Midland (+83%) and Devon & Somerset (RR = +36%). These are the areas that would expect a higher probability of having an RR exceeding the value of 1 (see Fig. 4).

On a year-on-year basis, the increased risks of fire-related dwelling casualties are significantly sustained throughout the 10-year period for Humberside, Lancashire, Greater Manchester, Merseyside, Tyne & Wear, West Midlands, West Yorkshire, and Devon & Somerset (as of 2011) (Table 5). The annual risk maps were enclosed in Appendix E.

## 5. Discussion

To our knowledge, this is the first study to bring together fire casualty information with the Index of Multiple Deprivation to explore the relationships between risk factors related to socioeconomic level and DF casualties. The results show that living environment and education are the predominant factors that influence the casualty risk related to DF, as shown in Table 4. The living environment index was measured based on the underlying indicators, including both indoors living environment (such as houses without any central heating and homes classified as 'poor condition') and outdoor living environment (e.g., air quality and road traffic accidents) which could be the explanation of this result. The indoor indicators specifically have a direct impact on the DF casualty risks (i.e., Houses with the poor living environment are more likely to result in fires with higher casualties due to more electrical heating use and rapid spread between houses (Marty, 2013; Spearpoint & Hopkin, 2020; Xiong et al., 2017)).

The finding for education conflicts with previous studies, as our research verified that education is a dominant positive factor for casualty risk. This may be because educational attainment affects people's fire prevention awareness (i.e., people with higher educational levels are probably more likely to use the qualified appliance and install smoking alarm (Jonsson et al., 2017; Thompson et al., 2018; Warda & Ballesteros, 2007), mitigation actions during the event of fires in home (i.e., being more educated might increase the reaction speed and the fire extinguished before it widely spreads) and the likelihood of excessive alcohol and tobacco use (i.e., people with less education are more likely to drink and smoke heavily, thus increasing their chances of becoming fire casualties (Ballard et al., 1992; Marshall et al., 1998; Pampel & Denney, 2011)).

The result shows that fire casualty risk is negatively correlated with the Barriers to Housing and Public Services domain in Table 3. To further explore this, we included this variable with all other IMD indicators in the multivariate model – the association became positive (see Table 4). The conflicting results might be due to the variable drawing on both positive and negative indicators (household overcrowding, homelessness, and housing affordability are used to derive the variable), that is, being homeless means having no abode, thus unlikely to experience a dwelling fire and becoming a fire casualty; in contrast, living in an overcrowded home means more people who could accidently or deliberately cause a dwelling fire, and thus it leads to higher likelihood to become a casualty of a fire.

However, these explanations are based on logical conjecture, although most could be demonstrated by literature. Considering that dwelling fire is a multifactored event, and human behaviors play a contributing role, these conjectures need to be supported by other cross-sectional studies. The significance of this ecological study is more exploratory than explanatory.

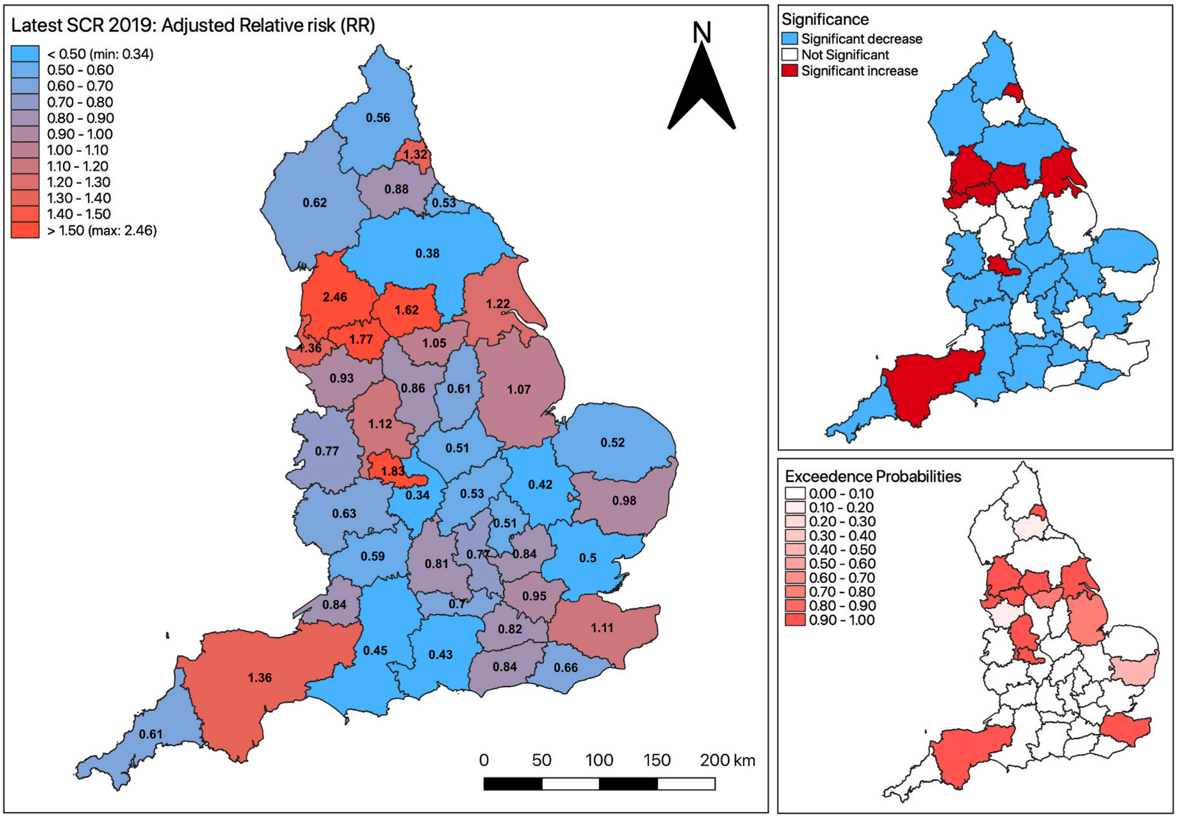


**Fig. 4.** Map shows the latest 2019 geospatial risk of fire-related dwelling casualties for each English FSAs in England (Left). The top-right panel shows the FSAs where the relative risks (RR) for such outcomes are statistically significant. The bottom-right panel shows which FSAs where you would expect the RRs for fire-related dwelling casualties to exceed the value 1.00. These are quantified as exceedance probabilities.

Additionally, the regions with obvious high risk and the sustained levels of increased risks across the years have been highlighted by using the Spatial-temporal model with the Markov chain Monte Carlo method, and the influence of socioeconomic factors have been considered. It is suggested that more work is needed to refine the assessment models to better identify areas where risk exists. For example, we found Lancashire, Merseyside, Manchester, and West Yorkshire exhibits the highest increased risks and such risks appeared to be clustered in these locations at an FSA-level (see Fig. 4). The authors concede to the fact that this estimation can be extended and vastly improved by measuring the risks using smaller geographical units if possible, to a Lower Super Output Area (LSOA, England's lowest spatial boundary) or even using exact point locations of properties.

### 5.1. Implications to practice

An implication of this is the possibility that assessing DF casualty risk through spatial-temporary modeling is a useful process to understand and measure the dynamic risk distribution, and consequently the risk map can help to implement fire safety interventions and design targeted policy in areas at high risk. Although this study was unable to present a lower-level risk distribution due to data limitations, this approach could easily be replicated in relevant local bureaus, such as FRSs, to draw the higher resolution maps for providing a more direct basis for action.

From a planning perspective, these maps of fire casualty risk probabilities across England are of practical and operational value to fire agencies as they provide evidence to help develop fire risk mitigation plans and improve the efficient use of resources (Ardianto & Chhetri, 2019), such as taking the socioeconomic factors into account for allocating the fire stations and equipment resources, especially for the unveiled high-risk probability areas. Besides, considering different deprivation levels have various impacts on casualty risk, this strategy can enable the FSAs to adjust the fire intervention strategy according to the feature of the area and the different high-risk social groups. In addition, understanding which areas have entrenched high risks of DF casualties over time can ensure prevention and mitigation efforts are targeted to areas most in need.

From a policy perspective, the analysis of historical fire incident data has generated new evidence that may help to address some of the policy questions that were not previously answered (Ardianto & Chhetri, 2019). Looked through the lens of socioeconomic deprivation, dwelling fire risks are more likely related to underlying social and historical processes than pure accidents. Therefore, mitigating the risk of fire casualties must be approached in a holistic way rather than treated as an engineering problem. This could be done by improving the social system. For example, relevant policies can be developed by tracing indicators that contribute to the problem in high-risk areas such as the living environment. In turn, policies helping to improve housing conditions and the wider living environment would reduce fire casualty risk.

The fire prevention strategies should also consider the appropriate allocation of medical resources, particularly in high-risk areas, because first-aid and aftercare are essential factors for the fire casualty risks. For example, people living in areas lacking a specialist NHS burns unit could be disadvantaged when it comes to receiving prompt and adequate medical treatment. In this case, our results can play an important role in informing collaborations with NGOs to relocate alternative medical resources, raise fire relief funding, provide first aid, provide practical and emotional support to people affected, and organize volunteers.

While the current findings provide valuable insights into spatial-temporal patterns of dwelling fire events, further work is needed to confirm the results and expand our understanding of the problem. Researchers, fire departments, and the public must continue their efforts to reduce (i) loss of life, (ii) the number of dwelling fires, and (iii) property

**Table 5**
Table shows the FSA and year-specific risk trajectories of SCRs in English; The colour blue indicates that the risks for casualties were significantly low for that FSA and year (RR < 1). The colour white indicates that such risks for casualties for the that FSA and year were not significant. The colour red indicates that the risks for casualties for that FSA and year were significantly high (RR > 1).

| English Fire Service Area (FSA) | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|
| Avon | White | White | White | White | White | White | White | White | White | White |
| Bedfordshire and Luton | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Royal Berkshire | Blue | Blue | Blue | White | White | Blue | Blue | Blue | Blue | Blue |
| Buckinghamshire and Milton Keynes | Blue | Blue | Blue | Blue | Blue | White | Blue | Blue | Blue | Blue |
| Cambridgeshire and Peterborough | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Cheshire | Blue | Blue | Blue | Blue | White | White | White | Red | White | White |
| Cleveland | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Cornwall | White | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Cumbria | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Derbyshire | White | White | White | White | White | White | White | White | White | White |
| Devon and Somerset | Blue | Blue | Blue | Red | Red | Red | Red | Red | Red | Red |
| County Durham and Darlington | White | White | White | White | White | White | White | White | Blue | White |
| East Sussex | White | Blue | Blue | Blue | Blue | White | Blue | Blue | Blue | Blue |
| Essex | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Gloucestershire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Hampshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Hereford and Worcester | White | White | White | White | Blue | Blue | Blue | Blue | Blue | Blue |
| Hertfordshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | White |
| Humberside | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| Kent and Medway Towns | Blue | Blue | Blue | Blue | Blue | Blue | White | White | White | White |
| Lancashire | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| Leicester, Leicestershire, and Rutland | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Lincolnshire | White | White | White | White | White | Red | White | Red | White | White |
| Norfolk | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| North Yorkshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Northamptonshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Northumberland | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Nottinghamshire and City of Nottingham | White | White | White | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| Oxfordshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | White |
| Shropshire and Wrekin | Blue | Blue | Blue | White | White | White | White | White | White | Blue |
| Stoke-on-Trent and Staffordshire | Blue | White | White | White | White | White | White | White | White | White |
| Suffolk | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | White | White |
| Surrey | Blue | Blue | White | Blue | White | White | White | Blue | Blue | Blue |
| Warwickshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |
| West Sussex | White | Red | Red | Red | White | White | Red | White | White | White |
| Greater Manchester | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| Merseyside | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| South Yorkshire | Blue | Blue | Blue | Blue | White | White | White | White | White | White |
| Tyne and Wear | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| West Midlands | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| West Yorkshire | Red | Red | Red | Red | Red | Red | Red | Red | Red | Red |
| London Fire & Emergency Planning Authority | Red | Red | Red | White | Red | White | White | Red | White | White |
| Dorset and Wiltshire | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue | Blue |

damage. In response to the increasing fire risk trend in England in recent years, there is a need to manage and maintain a broader fire infrastructure in all residential areas. In addition to the physical environment of cities, this study also highlights the need for social solutions.

### *5.2. Merits and limitations*

Internal validity is one of the strengths of our study. All the fire data used are from the official UK government website. To control the population difference, we chose Standardized Casualty Rate (SCR) as the risk indicator to measure the fire risk throughout the study, which is a fundamental determinant for the study accuracy. Moreover, although it is challenging to assess and measure the socioeconomic variables, the Index of Multiple Deprivation helped us solve this problem. However, in terms of external validity, its generalization is limited to other countries or regions with similar data and statistical caliber.

There is another merit from the study design. It is a new attempt to evaluate and simulate the time and geological features of DF casualties and social and economic factors that related to DF by using the spatial-temporal model, and the results indicate that there is a clear pattern to DF casualty risk in England with the consideration of social background. In the context of this study, compared with the traditional risk measurement method, the application of geostatistical and multiple variables has improved the accuracy of the model.

One limitation comes from the data itself. For the IMD data, we selected the index from the seven domains (i.e., living environment) instead of the underlying indicators (i.e., housing condition), although the latter might be better to explore the direct impact of socioeconomic variables on fire casualty risks. This is limited by the data availability; the indicators have been modified and added since 2015; thus the underlying indicators are not available in 2010 IMD data (Smith et al., 2015). Similarly, as the indicators of the data have been changed over the decade, the validity of the data has been reduced, which is another limitation. Besides, the lack of independence of the IMD domains may impact the result due to the similar underlying indicators used for multiple domains. For example, the Jobseeker's Allowance has been used for measuring both employment (contribution-based) and income domains (income-based), which result in the very strong statistical relationship between the domains (Department for Communities & Local Government, 2017; Ministry of Housing & Communities & Local Government, 2015). To mitigate this problem, we have checked the multicollinearity among the domains. In addition, it is difficult to give further interpretation for the temporal side because the time scale is too short and has limited meaning due to data availability. While we found the increased year-on-year risks for each fire service area, the underlying reasons for this are hard to know. It could be improved by changing the data from year to quarter to find seasonal differences.

Finally, another potential flaw about this study is that we had to aggregate the IMD score data to FSAs which is a much lower resolution than the LSOA (which it was originally calculated as) because fire casualty data are collected in units of FSAs. On top of that, the framework of this study is typically an ecological study design dealing with aggregated units of casualty data to a geographic level as opposed to fire events occurring at an individual or residential property level. All inferences are made areal-wise, which is not exactly true when examining at a much granular level. Therefore, the 'ecological fallacy' probably existed in this study.

Although we have several limitations due to the data limitations, the importance and originality of this study are that it explores the DF casualty risk by using contemporary epidemiologic methods and provides innovative insights for future studies. Thus, strengths outweigh weaknesses.

## 6. Recommendations

Based on the analysis above, the following suggestions for future research are drawn: 1.) further study needs to be done to reinforce our findings; 2.) Under the Bayesian framework, a longitudinal framework with high-resolution data (i.e., point patterns of fire occurrence) are needed. Bayesian modeling such as the INLA-SPDE (i.e., Stochastic Partial Differential Equations) may prove a robust and flexible approach for producing surface predictions of the risks of incident fire hazards. This could help us to explore and understand the temporal factors that contribute to fire casualties, such as breaking down time units into seasons or months, in order to identify high-risk months in time in England and speculate about the underlying links to climate or weather. In the horizontal study, the various fire service areas need to be refined, such as classifying them into urban and rural areas or calculating the residential coverage rate and population density. By refining the differences between regions, we can find out the reasons for regional differences to give specific preventive measures. After more detailed and specific reasons are found, the model could be modified to measure posterior risks among England to further explore and design targeted policy for each county.

## 7. Conclusion

The results in this study largely supported the previous research on dwelling fire that the association between the socioeconomic variables measured by the IMD and SCR is significant and demonstrated the dwelling fire casualty risk in England has a clear temporal and spatial pattern over the last decade. Using the spatial-temporal Bayesian regression model, the trajectories, and levels of sustained risk of SCRs throughout the areas in England have been mapped and plotted considering the impact of socioeconomic variables while the high-risk areas have been highlighted. Notwithstanding the limitations lying in the availability and different caliber of the data, this study proved the feasibility of the spatial-temporal model on fire casualty research which will assist the improvement of future risk identification models and fire prevention strategies. Future work could still take the form of computational models and aim to develop knowledge of the fundamental casualty causing reasons and social background involved in each area.

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## CRediT authorship contribution statement

**Lan Li:** Methodology, Software, Data curation, Formal analysis, Writing – original draft, Visualization. **Anwar Musah:** Methodology, Software, Data curation, Formal analysis, Writing – original draft, Visualization. **Matthew G. Thomas:** Conceptualization, Writing – review & editing. **Patty Kostkova:** Conceptualization, Writing – review & editing, Supervision.

## Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Appendices. Supplementary data

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