Mapping the Spatio-Temporal Distribution of Rough Sleepers in London: An exploration of the CHAIN dataset

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Abstract

Rough sleeping is one of the major public health crises facing world cities and continues to worsen. The Combined Homelessness and Information Database (CHAIN) collates information on rough sleepers in London, collected by outreach reams day centres and other projects. Using a spatio-temporal Bayesian Hierarchical model, this paper examines the trends in rough sleeping in London from 2005-2016, as they are represented in CHAIN.

Keywords: Rough sleeping, homelessness, Bayesian, Spatio-temporal, INLA

1. Introduction

Rough sleeping is one of the major public health crises facing world cities and continues to worsen. The England yearly snapshot estimate of rough sleepers collected by the Department for Communities and Local Government rose from 3,569 to 4,134 between Autumn 2015 and Autumn 2016, a 16% increase (DCLG, 2017). Yet the true extent of the issue may be far worse than official statistics reveal. A 2015 report by the UK Statistics Authority revealed that Homelessness Prevention and Relief and Rough Sleeping statistics did not meet the standard to be National Statistics (UKSA, 2015). The Combined Homelessness and Information Network (CHAIN), which uses outreach teams to collect rough sleeping statistics in London, had contact with a total of 8,096 rough sleepers during 2015/16 (financial year), a 7% increase on 2014/15. Of these, 5,276 were categorised as new rough sleepers (GLA, 2016). There is clearly a mismatch between official recording of rough sleeping statistics and the reality of the situation on the UK's streets. This paper presents the first analysis of the historical spatio-temporal trends in rough sleeping at the London borough level as they are represented in CHAIN. A hierarchical Bayesian approach is used to generate probability of exceedance of London wide rates and these are discussed.

1.1. The CHAIN dataset

The Combined Homelessness and Information Network (CHAIN) is a multi-agency database managed by St Mungo's, and funded and commissioned by the Greater London Authority (GLA) (St Mungo's, 2017). The database records information on rough sleepers across all 32 London boroughs as well as the City of London, collected by outreach teams, day centres, accommodation projects and other projects such as No Second Night Out (NSNO, 2012). CHAIN is continually updated and provides insights into the spatiotemporal distribution of rough sleepers that the annual national street count statistics cannot reveal. For the purposes of this study, the CHAIN data provided by St Mungo's are counts of rough sleepers at the borough level, monthly, from January 2005 to May 2016.

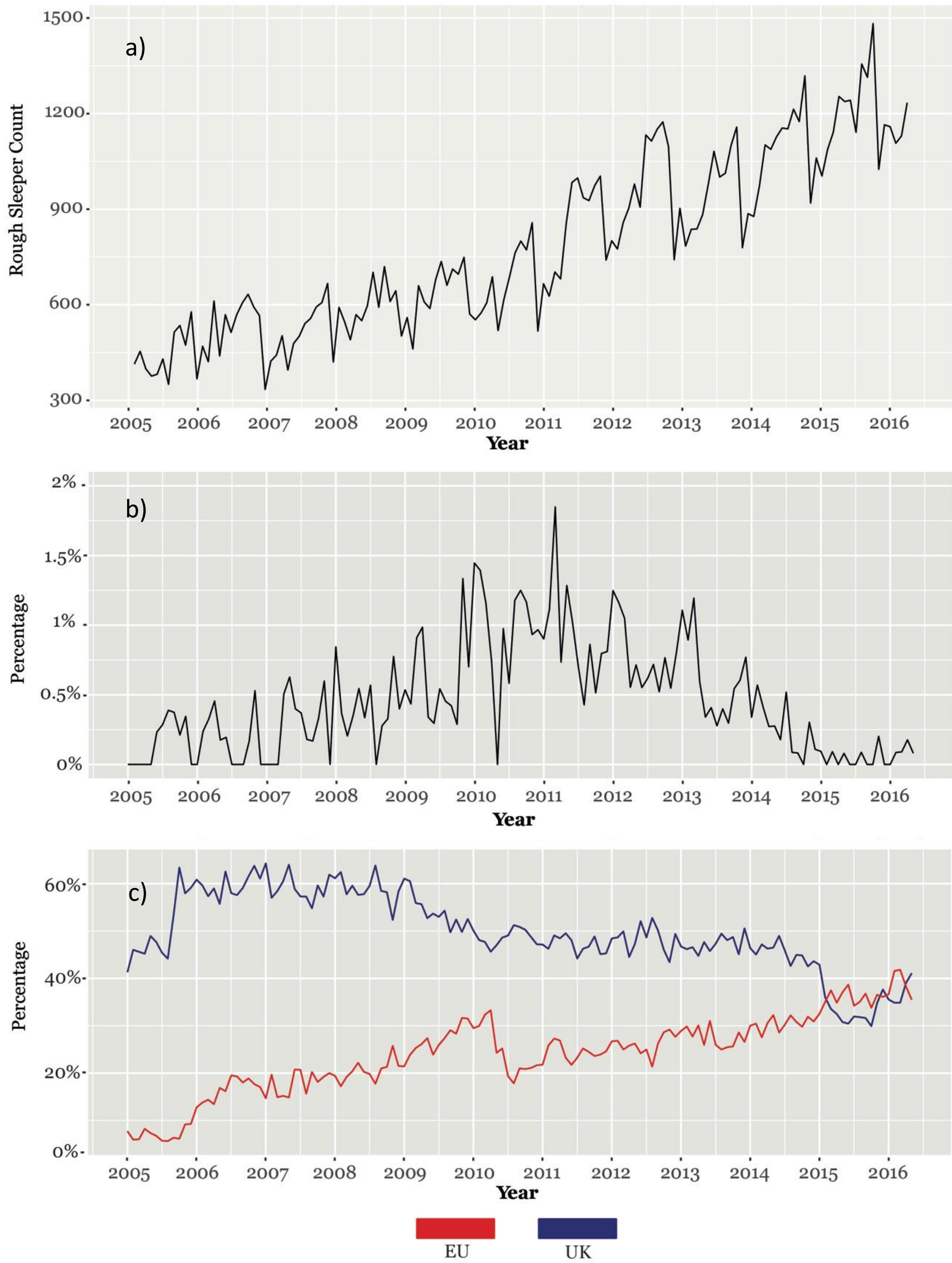

Figure 1: Notable temporal trends in the CHAIN dataset: a) number of rough sleepers recorded in CHAIN; b) percentage of individuals seen rough sleeping more than 10 times per month; c) percentage of UK and EU (excluding UK) rough sleepers

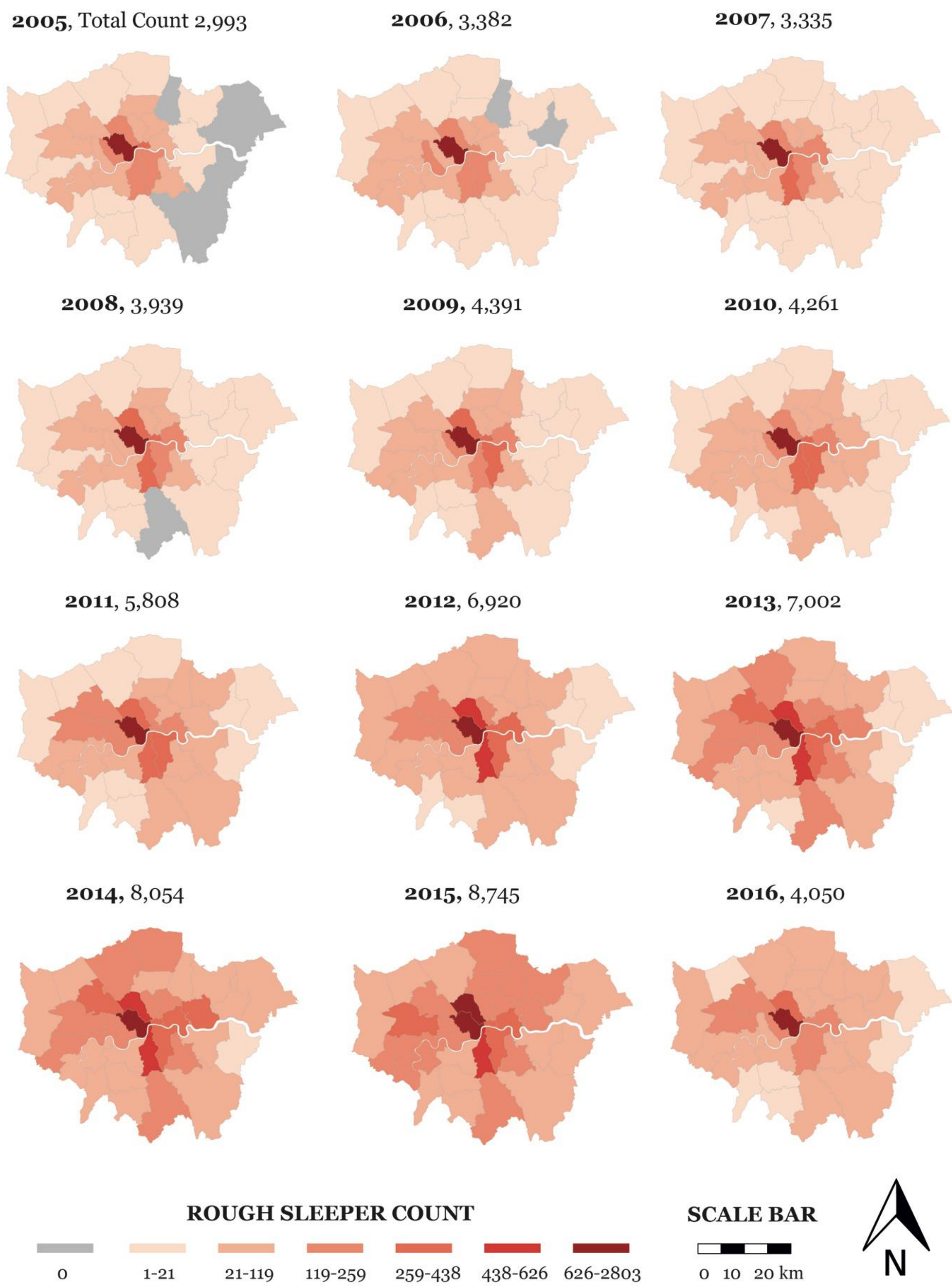

Figure 2: Spatial distribution and count of rough sleepers recorded in CHAIN, 2005-2016. Note that borough total counts are the sum of borough totals and individuals may be counted more than once if appearing in multiple boroughs during a single month.

Figures 1 and 2 show the temporal and spatial trends in the CHAIN dataset between 2005 and 2016 (note 2016 is partial data). A temporal trend of increasing numbers of rough sleepers recorded in

CHAIN is apparent, with a spatial concentration in Westminster. It should be noted that this increase does not take into account changes in outreach teams' activities, which will be discussed later. Interestingly, the percentage of rough sleepers seen more than 10 times in a month rose until the early part of 2011, before steadily declining to the present. This corresponds with the launch of the Greater London Authority's (GLA) NSNO initiative on the 1st April 2011 (NSNO, 2012).

2. Methodology

This study applies a spatio-temporal Bayesian hierarchical modelling approach to rough sleeper counts obtained from the CHAIN database at the borough level. In the context of rough sleeping, this type of model can be used to reveal those locations and times where there is increased risk of higher than expected rough sleeping rates. The model is applied to yearly counts between 2005 and 2016 for the 32 London Boroughs as well as the City of London. The mean number of rough sleepers λ_{it} in borough i at time t is assumed to be Poisson distributed. The mean can be expressed in terms of the rate of rough sleeping θ_{it} multiplied by the expected number of rough sleepers e_{it}. A linear predictor is defined on a logarithmic scale. The form of the model is as follows (for more details see (Blangiardo and Cameletti, 2015, p. 241):

$$\log(\theta_{it}) = b_0 + u_i + v_i + y_t + \phi_t + \delta_{it}$$

Equation 1

Where:

θ_{it}= The rough sleeping rate in borough i at time t.
u_i= spatially structured term, $u_i|u_{i\neq j} \sim Normal(m_i, s_i^2)$ following the Besag-York-Mollie (BYM) specification (Besag et al., 1991) with intrinsic conditional autoregressive structure (iCAR) with $m_i = \frac{\sum j\neq N(i) v_j}{\#N(i)}$ and $s_i^2 = \frac{\sigma_v^2}{\#N(i)}$ where $\#N(i)$ is the number of neighbours of location i.
v_i= spatially unstructured random effects term with Gaussian exchangeable prior $v_i \sim Normal(0, \sigma_v^2)$
y_t= first-order random walk-correlated time term $y_t|y_{t-1} \sim Normal(y_{t-1}, \sigma^2)$
ϕ_t= an uncorrelated random time variable with Gaussian exchangeable prior $\phi_t \sim Normal(0, \tau_\phi)$
δ_{it}= space-time interaction term that assumes v_i and ϕ_t interact and $\delta_{it} \sim Normal(0, \frac{1}{\tau_\delta})$

The spatial arrangement of the boroughs is encoded in an *n*n* spatial adjacency matrix **W**, where$w_{ij} = 1$ if two boroughs share a border, 0 otherwise. **W** is used in the spatially structured term. All experiments are carried out in R-Studio (R Studio Team, 2015). The model is trained using integrated nested Laplace approximation (INLA) using the R-INLA package (Blangiardo et al., 2013). W is generated using the spdep package (Bivand, 2008).

3. Results

Exponentiating the intercept b_0 reveals a London wide rough sleeping rate of 0.38%. Figure 3 shows the probability of each borough exceeding twice this rate. The highest spatial risk is concentrated in the central boroughs. This is consistent with observations of rough sleeping in London, which tends to be concentrated around the borough of Westminster. Time series analyses for these 7 central boroughs between 2005 and 2015 reveal consistently high rough sleeper counts with a general upward trend. Time series analyses for the boroughs of Ealing, Islington and Brent, indicated as having a moderately high level of risk for exceeding twice the London wide rough sleeper rate, show that significant increases have occurred since 2010. Brent in particular has reported that during the summer months, a significant number of migrant workers have been recorded rough sleeping in parks (Safer Brent Partnership, 2015). This may account for some of the increase.

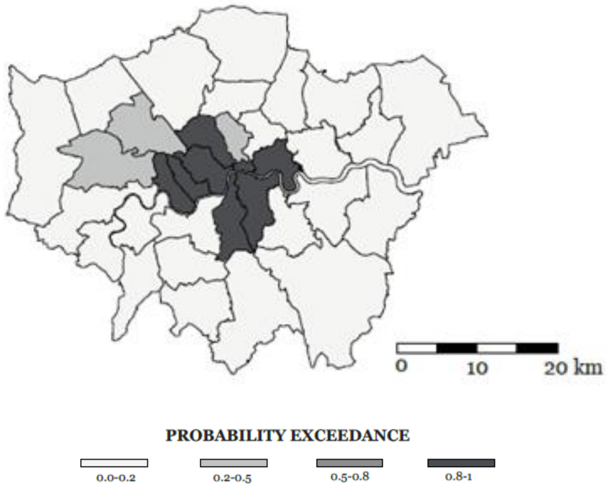

Figure 3: Probability of exceeding twice the London-wide rough sleeping rate

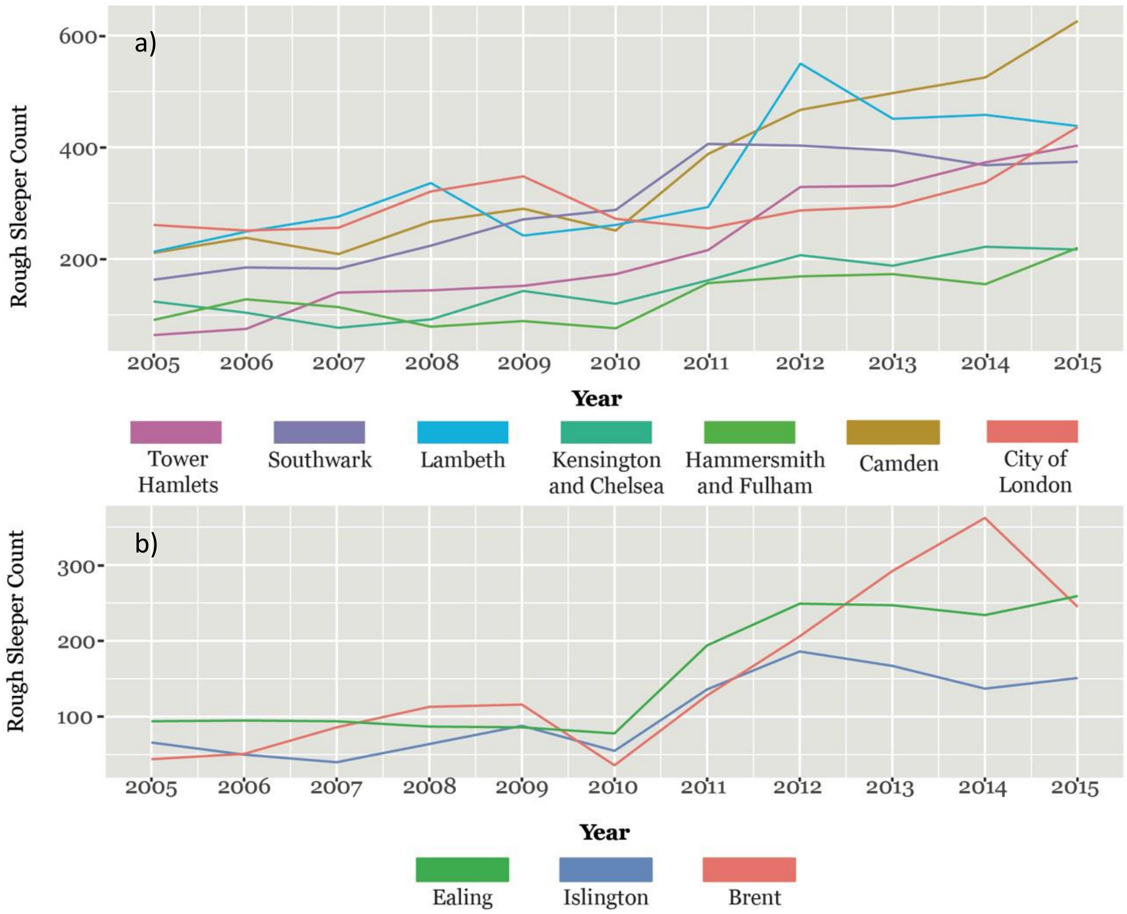

Figure 4: Time series of rough sleeper counts of a) boroughs with the highest risk and b) boroughs with increasing risk

The temporal component of the model captures the large increase in rough sleeping risk across the study period (figure 5). The most significant increase occurred between the years of 2011 and 2014. Figure 6 overleaf shows the space-time interaction term for each of the years in the data. Boroughs with posterior probability estimate of greater than 0.5 of exceeding a relative risk greater than 2 in a particular year generally correspond to significant increases in rough sleeper counts compared with previous years. For example, rough sleeper counts in the Borough of Croydon in 2009 and Havering in 2010 increased from 0 (in 2008) to 44 and 5 (in 2009) to 14 respectively. Some of these increased counts may reflect the effect of having more outreach teams or volunteers recording information on rough sleepers. For example, before 2009, Croydon had no dedicated outreach team, resulting in little information being recorded about rough sleepers there.

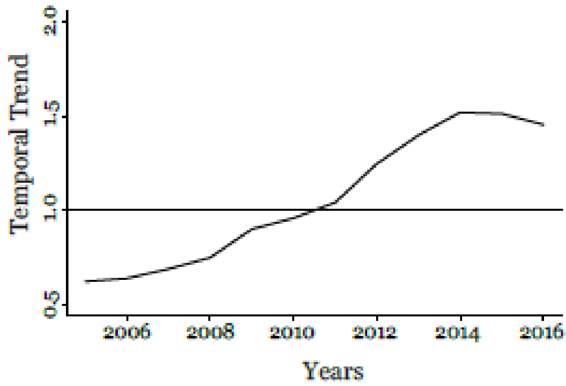

Figure 5: Temporal component of the model

4. Conclusions

This paper reveals some of the spatio-temporal trends present in rough sleeping in London based on the CHAIN dataset. Overall, an increasing trend in rough sleeping is apparent. The central boroughs consistently have highest risk, but there is a trend of increasing risk in peripheral boroughs such as Ealing, Islington and Brent. It is important to note that the trends here do not account for variations in the number, size or spatial distribution of outreach teams as that information is not currently available. The authors are working with the curators of CHAIN to collate information on outreach teams' activities, which will be incorporated into the model in future work. This will enable extrapolations to the total number of rough sleepers as well as forecasts. Changes in data collection methods since the beginning of 2016 allow the CHAIN data to be recorded at higher spatial resolutions and the authors plan to extend their analyses to middle layer super output area level in the future.

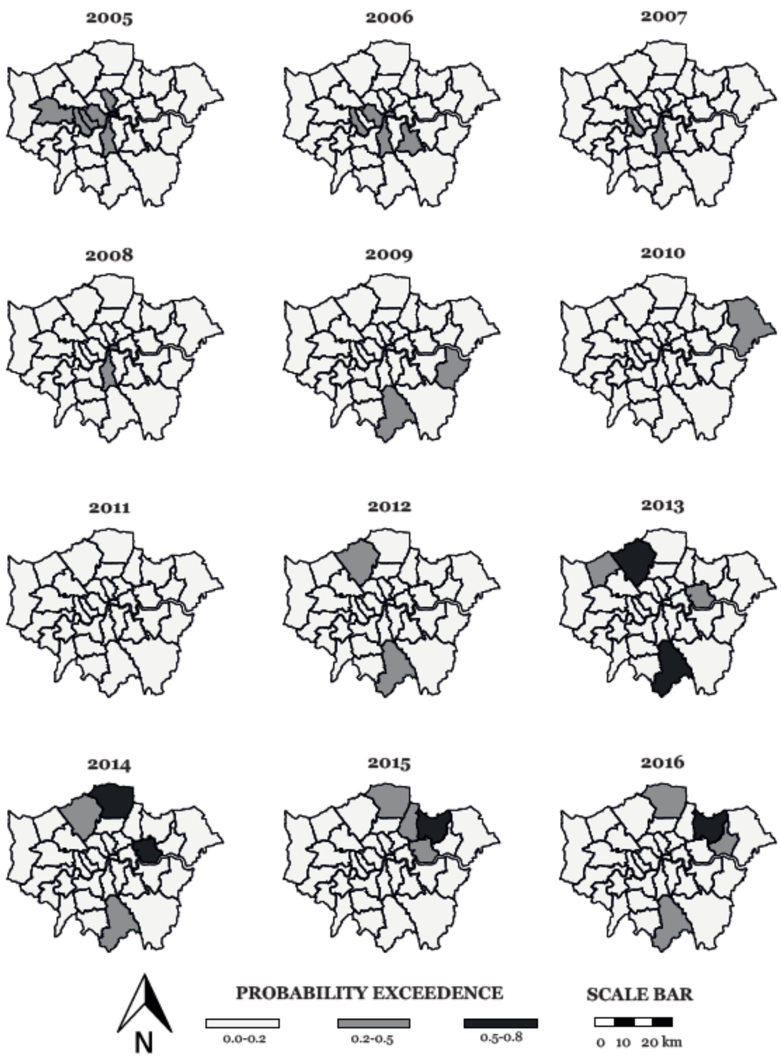

Figure 6: Probability exceedance >2 between 2005 and 2016, space-time interaction term.

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