Predicting public confidence in the police with spatiotemporal Bayesian hierarchical modelling.

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Summary

Public confidence in the police is crucial to effective policing. Estimating and predicting public confidence at the local level will better enable the police to conduct proactive confidence interventions to meet the concerns of the community. This work represents the first application of Bayesian spatio-temporal modelling to estimation and prediction of public confidence in the police at the local level. Three models of increasing spatiotemporal complexity were fitted by Markov chain Monte Carlo simulation using free software package WinBUGS. Public confidence was successfully predicted at the local level using a spatiotemporal model with an inseparable interaction structure.

KEYWORDS: spatiotemporal, Bayesian hierarchical model, public confidence, policing, prediction

1 Introduction

Public confidence in the police is crucial to effective policing. Improving public confidence facilitates a better relationship between the police and the public at large, increasing the likelihood of them coming forward with tips, obeying the law or joining the force as volunteers (Association of Chief Police Officers 2012) (E. A. Stanko and Bradford 2009) (Tyler and Fagan 2008). This is particularly relevant within the context of the British model of "policing by consent" (Jackson et al. 2013).

The spatiotemporal variability of public confidence has only recently been established (Williams, Haworth, and Cheng 2015). Prior to this a time-series approach at the aggregate level was taken by Sindall, Sturgis, and Jennings (2012). In this work a hierarchical Bayesian spatio-temporal approach is used to estimate and predict confidence levels at the local level. These more detailed predictions can be leveraged to plan and execute targeted public confidence interventions in the community.

This study focuses on attitudes toward the London Metropolitan police (MET) for whom public confidence is one of the most important issues. The Mayor's Office for Police and Crime (MOPAC) Public Attitudes Survey (PAS) data is used. The MOPAC PAS surveys the experiences and perceptions of Londoners with respect to crime, policing and anti-social behaviour. It is unmatched worldwide in the amount of data collected. Exploratory spatiotemporal data analysis is used to understand the underlying spatiotemporal autocorrelation structure. We assess the predictive performance using the Coefficient of Determination (COD) and the goodness of fit using the Deviance Information Criterion (DIC). Further spatiotemporal autocorrelation analysis is performed on the residuals of the models.

2 Estimating and predicting public confidence in the police in space-time

This section describes the procedure used for estimating and predicting public confidence in the police at the small area level using a spatio-temporal Bayesian hierarchical modelling approach.

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1.1 Study Area

The study area is London, the capital city of the United Kingdom. London is divided into thirty-two boroughs and 628 census area wards. A ward is roughly equivalent to a neighbourhood. In addition to reporting confidence levels at the borough level, MOPAC reports confidence values using a sub-borough level areal unit called the borough neighbourhood (Mayor’s Office for Policing and Crime 2016). The borough neighbourhood is comprised of two or three wards.

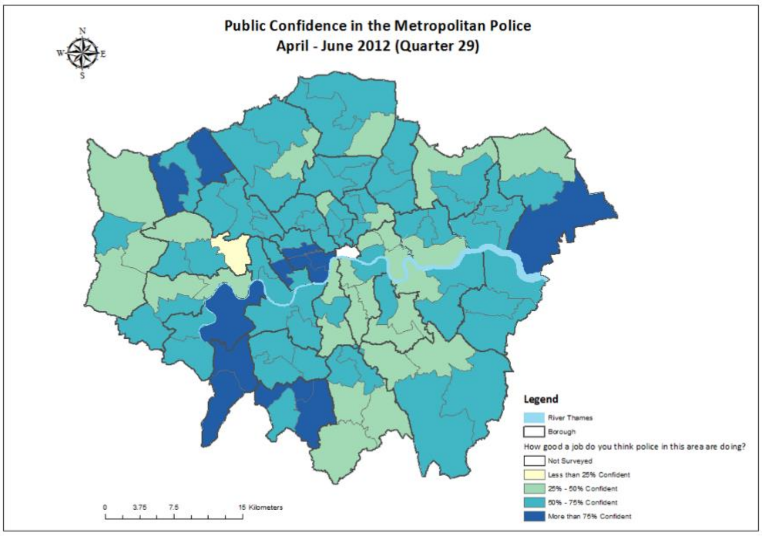

Figure 1 Map of MET Borough neighbourhoods showing confidence in the police April – June 2012.

1.2 Dataset

The Metropolitan Police Public Attitudes Survey (PAS) has been conducted since 1983 (Mayor’s Office for Policing and Crime, 2014b). The survey is performed on a rolling basis, with results reported quarterly and annually. A quarterly temporal unit is chosen for this study. Face-to-face interviews of approximately 100 persons per quarter are conducted (BMG Research 2012). Question 60, which asks how “good a job the police are doing in this area”, is the focus of this study. A respondent is confident if they state that the police did an “excellent” or “good” job and a Borough neighbourhood considered confident if at least 75% of respondents are confident (Mayor’s Office for Policing and Crime 2013a). An investigation into the reliability of the responses to question 60 falls outside the scope of the study. In a practical sense, MOPAC compares the responses with those obtained from the Crime Survey for England and Wales, a national survey with a comparable aims and methodology.

The PAS is designed to be representative and accurate at Borough level (BMG Research 2012). Consequently, the number of respondents per Borough neighbourhood is quite variable. Figure 2, a box and whisker plot of the number of respondents, highlights this.

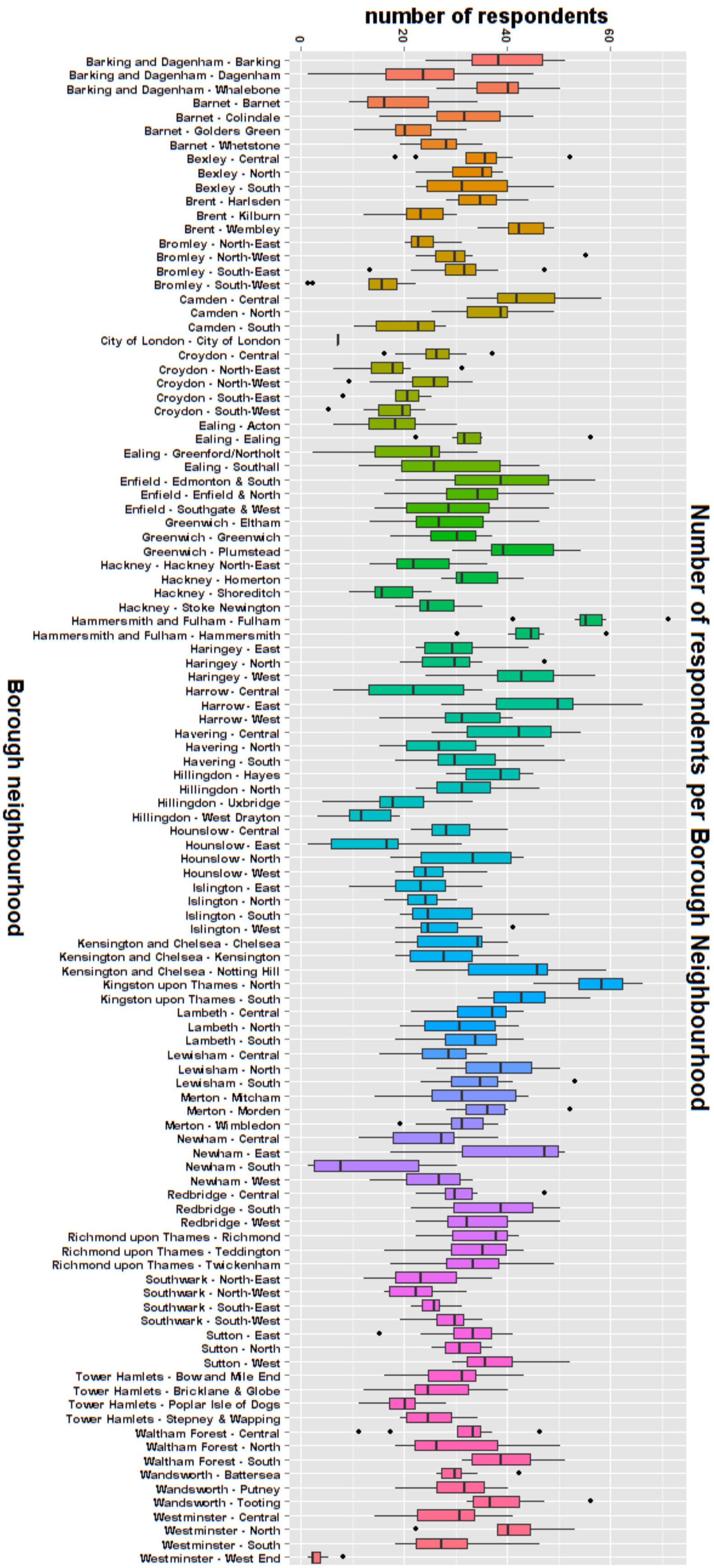

Figure 2 Number of respondents per Borough neighbourhood

This variability leads to unstable estimates and predictions. This study exploits a Bayesian hierarchical modelling approach to overcome this enabling the use of PAS to be extended to the small area level.

1.3 Spatio-temporal Bayesian hierarchical modelling

The hierarchical modelling framework has been identified as the ideal vehicle for transferring spatiotemporal statistical methodologies into the realm of social science survey analysis (Wikle, Holan, and Cressie 2013). A Bayesian hierarchical approach is particularly suited to this study as it allows information to be shared across areal units, compensating for unstable/ missing data (Gelman and Price 1999). Spatiotemporal Bayesian hierarchical modelling is still a fairly new approach. Notable examples of its use for modelling non-normally distributed (count) data include modelling disease risk (Knorr-Held 2000), burglary (Li et al. 2014), cycle accidents (DiMaggio 2015) and election polls (Shor et al. 2007a).

The spatiotemporal modelling approach used is described below. Conducting an attitude survey can be considered a Bernouilli trial where a confident response is considered a success. The likelihood of obtaining *y* successes in *n* trials is modeled via a binomial probability distribution (Equation (1)). y_{it}, the response variable, is the number of confident respondents in Borough neighbourhood $i = 1, \ldots, 108$, in $t = 1,\ldots,20$ quarters and π_{it} is the probability that Borough neighbourhood i will be confident in quarter t .

$$y_{it} \sim Binomial(n_{it}, \pi_{it}) \tag{1}$$

Due to the fact that count data is non-normally distributed, a generalized form of equation 1 is used. This generalized form is obtained by applying a logit transformation (equation 2). For further details see Rodríguez (2007).

$$n_{it} = logit(\pi_{it}) = log\frac{\pi_{it}}{1-\pi_{it}} \tag{2}$$

The generalized form is then expressed as an additive function of spatial or spatiotemporal covariates. This is performed in equations 3 – 5 where α is an intercept term, U_i represents spatially unstructured random error, S_i represents spatially structured random error, v_t represents temporally structured random error and δ_{it} is a spatiotemporal interaction term. The Intrinsic Conditional Autoregressive (ICAR) prior (Besag and Kooperberg 1995), was chosen for S_i; a random walk prior was used to represent temporally structured random effects, v_t; and a normally distributed prior was used for δ_{it}.

Equation 3, commonly referred to as a BYM model after the initials of authors Besag, York, Mollié (1991) relates the generalized form to purely spatial covariates. In equation 4 the covariates may be said to have a separable spatio-temporal structure as the covariates may be neatly decomposed into purely spatial and purely temporal components. Equation 5 may be described as having an inseparable spatiotemporal structure due to the addition of the spatiotemporal interaction term. Inseparable spatiotemporal interaction structures have been classified by Knorr-Held (2000). According to this classification Model 3 has Type I spatio-temporal interactions.

Model 1 $$logit(\pi_{it}) = \alpha + (U_i + S_i) \tag{3}$$

Model 2 $$logit(\pi_{it}) = \alpha + (U_i + S_i) + v_t \tag{4}$$

Model 3 $$logit(\pi_{it}) = \alpha + (U_i + S_i) + v_t + \delta_{it} \tag{5}$$

Explanatory variables (covariates) may be added to the model as fixed effects. As the purpose of this study is to demonstrate a novel approach to modelling public confidence in the police rather than investigate associations with other factors, a purely autoregressive approach was taken.

1.4 Implementation

The three models were implemented in WinBUGS, Windows based freeware package for building and analysing Bayesian probability models with Markov chain Monte Carlo techniques (Lunn et al. 2000). In all cases, two Monte Carlo chains were used, and 18,000 iterations were performed after convergence. Convergence of the chains was checked with three measures: visually with trace plots and the visual representation of the Gelman-Rubin $\hat{R}$ statistic as well as by ensuring that the Monte Carlo error was less than 5% of the posterior standard deviation.

1.5 Evaluation framework

The data was split (2:1) into training and test data to allow for model evaluation: the first 20 quarters were used to train the model which then predicted 10 quarters into the future. The predictive accuracy was evaluated using the coefficient of determination (R^2). The R^2 statistic is a proportional measure of goodness of fit where values close to 1 suggest that a large amount of variability was captured within the model (James et al. 2013).

The Deviance Information Criterion (DIC) was used to ensure the most parsimonious and generalizable model was chosen. The DIC equation 5, is a likelihood based measure of model complexity where $\bar{D}$ denotes goodness of fit and p_D is a Bayesian measure of model dimensionality (Spiegelhalter et al. 2002).

$\bar{D}p_D$

$$\mathrm{DIC} = \bar{D} + p_D \tag{5}$$

3 Results

The scatterplots of the predicted number of confident respondents vs actual number of confident respondents can be seen in figure 3. These show a good fit overall which indicates a strong correlation between the measured number of confident persons and the predicted number of confident persons. It can also be seen that the predictions obtained from the purely spatial model are the least accurate.

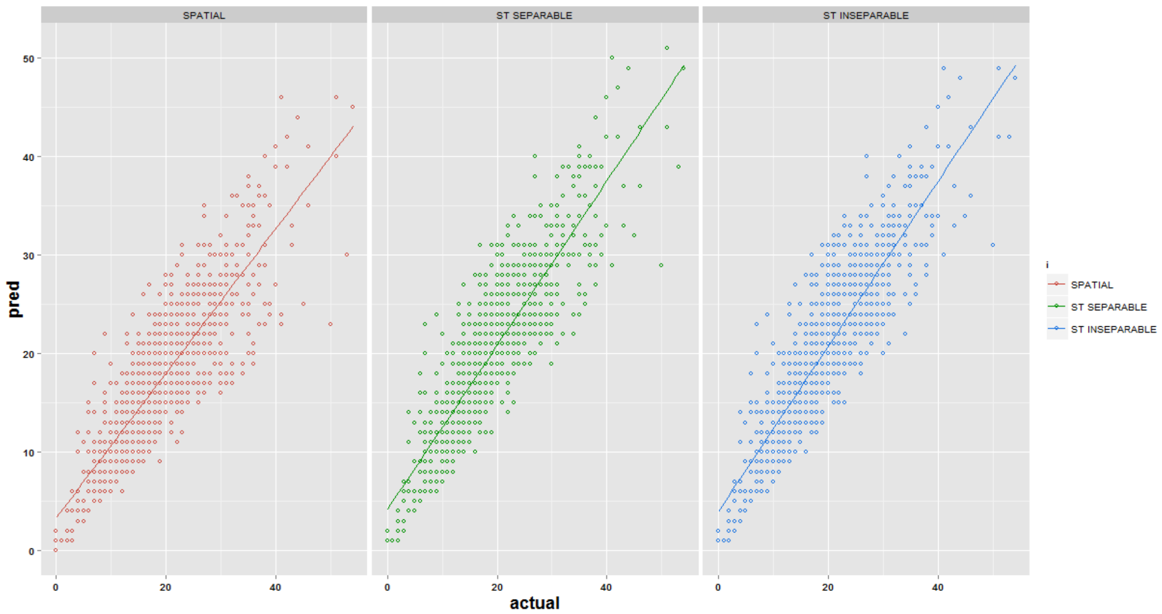

Figure 3 Scatterplot of predicted number of respondents versus measured number of respondents for the spatial, separable spatiotemporal and inseparable spatiotemporal models respectively.

Model evaluation statistics are presented in table 1. The models follow the expected trend: as the complexity of the model increases, the goodness of fit increases. However, the progressively lower DIC values reflect the increasing parsimony of the models even as the penalty for the increased complexity increases. The R^2_{test} values confirm that Model 3 is the most successful overall as the predictions obtained from Model 3 have the best goodness of fit explaining 76.7% of the inherent variability. The inclusion of the spatio-temporal interaction term δ_{it} increased the flexibility of Model 3, enabling the temporal trend of each neighbourhood to deviate from the trend of the overall mean and providing the most realistic estimates and predictions.

Table 1 Model evaluation statistics

Model	R^2_{test}	$\bar{D}$	p_D	DIC
Model 1: purely spatial (BYM)	0.699	24,393.5	936.433	25,330.0
Model 2: spatiotemporal separable	0.747	23,568.4	1,559.120	25,127.6
Model 3: Knorr-Held Type I	0.767	11,899.9	3,379.5	15,279.4

Public confidence in the police varies in space-time (Williams, Haworth, and Cheng 2015). This study exploited this autocorrelation to predict confidence at the local level using a Bayesian hierarchical approach. This methodology may be adopted by MOPAC to allow more targeted confidence interventions to be performed and should facilitate increased strides toward the goal of making the MET police the most loved force in the world (Mayor's Office for Policing and Crime 2013b).

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5 Biography

Dawn Williams is a PhD student at the SpaceTimeLab for Big Data Analytics (http://www.ucl.ac.uk/spacetimelab) at University College London. Her research interests include spatiotemporal data mining, Bayesian methods, visualization, big data analysis and sustainable development.

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