Small Area Estimation of Public Confidence

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Abstract

This paper explores the use of a spatiotemporal approach to small area estimation for improving understanding of attitudes to policing. The study focusing on confidence in the police in London using sample survey data. The Public Attitudes Survey (PAS) collects data on the experiences and perceptions of Londoners with respect to crime, policing and anti-social behavior. While the most robust survey of its kind in the world, it is not designed for use at the neighborhood-level but rather to produce annual, Borough level estimates on a rolling average basis. However, there is a demand for reliable, local level data for quarterly assessment and planning. In this study, we present a Bayesian spatiotemporal hierarchical modeling approach to small area estimation to address this. In this approach, information is "borrowed" from neighboring regions in space and time to increase effective sample size. This enables reliable estimates, forecasts and classification of trends in confidence at the neighborhood-level.

Keywords – forecasting, Bayesian, spatiotemporal, small area estimation, policing

1 Introduction

Public confidence in the police is a state in which the public regard the police as competent and capable of fulfilling their roles. This results from the police being effective in dealing with crime and anti-social behavior, as well as fair treatment of and engagement with the community. The British model of policing is underpinned by a philosophy of "policing by consent" whereby the police are empowered by the common consent of the public. The public observes the law as a result of their approval, respect, and affection for the police rather than compliance being motivated by fear. In this context, public confidence in the police is a key component of effective policing. Persons who are confident in the police are more likely to be cooperative, compliant and crucially to supply the tips which inform proactive policing operations.

The Mayor's Office for Policing and Crime (MOPAC) Public Attitude Survey (PAS) collects data on the experiences and perceptions of Londoners with respect to crime, policing and anti-social behavior. Understanding these patterns at the local level is an important step in developing a targeted confidence intervention strategy. While the most robust survey of its kind in the world, the PAS is designed to measure confidence at the Borough level on a rolling annual basis. This presents a challenge for policy makers and practitioners who wish to support decisions at an operational useful level. Improvements are required to support the demand for reliable, local level data for quarterly assessment and planning. An additional challenge to modelers is the fact that public confidence in the police varies across geographical space and over time (Williams, Haworth, and Cheng 2015). Methods are required which can overcome this data sparsity and also accommodate this spatiotemporal variation. We present a Bayesian hierarchical approach to small area estimation which overcomes these challenges.

2 Public Confidence in Policing

This study considers public confidence in the police in London, UK. London is home to 8.5 million inhabitants of diverse heritage and cultures (ONS, 2015). The Mayor's Office for Policing and Crime (MOPAC) provides strategic insight and resources for policing while the Metropolitan Police Service (MPS) is responsible for operational policing. MOPAC and the MPS have used surveys for public consultation since the 80s (Harrison, Dawson, and Walker 2009). The Public Attitudes Survey (PAS) is a large scale, rolling, population representative survey which collects opinions on policing, and has been its current form since 2002 (Harrison, Dawson, and Walker 2009). It is conducted face-to-face and is designed to be representative of the residents of London annually at the borough level (BMG Research, 2012).

MOPAC and the MPS use the question "Taking everything into account, how good a job do you think police IN THIS AREA are doing?" as a public confidence indicator. A respondent is confident if they state that the police did an “excellent” or “good” job. Figure 1 is a plot of the temporal trend of public confidence over the survey period at the London-wide level. Public confidence has steadily increased overall during the study period April 2006 - March 2015 but is on the decline from historically high percentages of 70% in March 2014.

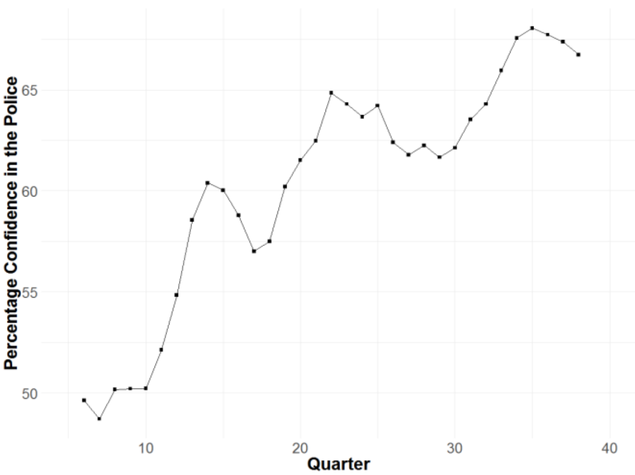

Figure 1: Time-series plot of London-wide probability of public confidence in the police April 2006 – March 2015

PAS survey data has been used to develop an evidence-based model of public confidence in the police by (E. A. Stanko and Bradford 2009). The model framework draws on Tyler’s motive-based trust theory (B. Stanko et al. 2012) as well as Stoutland’s four dimensions of trust (Stoutland 2001). The model identifies four drivers of public confidence: effectiveness in dealing with crime, engagement with the community, fair treatment, and alleviating anti-social behavior (E. A. Stanko and Bradford 2009). PAS data has also recently been used by to investigate effects of segregation and ethnic diversity on social capital (Laurence 2016).

MOPAC and the MPS have combined the wards into 108 larger units of operational significance called borough neighborhoods that consist of two or three wards (Mayor’s Office for Policing and Crime 2016). For simplicity, the term neighborhood will refer to this level of aggregation throughout this paper. With respect to temporal aggregation, MOPAC ties the analysis of public confidence in the police to the financial year, with performance figures collated four times a year. The study uses data collected over 36 financial quarters, spanning nine years between April 2006 (Q5) and March 2015 (Q40).

3 Method

Many government samples surveys are designed to provide statistically reliable estimates at the high-level geographies. Frequently, information at more detailed geographies is required. As the neighborhood context is central to perceptions of the police, neighborhood level intelligence is required (Jackson et al. 2013). This presents a challenge as the sample sizes are too small to produce statistically robust, neighborhood level estimates. In the past, survey data was often pooled with the assumption that the phenomenon being measured is stable. This assumption may not hold over time and/or over space (Brace et al. 2002). Small area estimation techniques are statistical approaches which increase the effective sample size at the neighborhood level by combining information from neighboring regions a process called “borrowing strength”. A spatiotemporal approach to small area estimation improves this “borrowing strength” process with the use of spatially and temporally correlated random errors (Jiang and Lahiri 2006). In this study, a Bayesian spatiotemporal approach to small area estimation is used for estimating patterns of confidence, forecasting these patterns into the future, examining hotspots and coldspots of confidence in space-time.

3.1 Spatiotemporal Estimation

The Bayesian approach to estimation is a mathematically compelling way to reallocate the credibility of several candidate outcomes given the data (Kruschke and Liddell 2017). A spatiotemporal Bayesian hierarchical approach developed by (Bernardinelli et al. 1995) will be used whereby the data is assumed to have a spatial trend common to all time periods, a temporal trend common to all areas and a space-time interaction term which allows time trends to differ locally. Neighborhood-level confidence values were modeled using a Binomial distribution. We then assumed our patterns could be estimated as a function of spatial random errors, temporal random errors component, and a dynamic spatiotemporal interaction component.

3.2 Spatiotemporal Forecasting

A forecast presents a picture of an uncertain future enabling wise decisions to be made (Harrison and West 1987). Forecasting with a Bayesian approach is achieved by considering future values of the phenomenon of interest as unknown quantities to be estimated. We applied this Bayesian approach to forecasting to produce quarterly, one-step ahead forecasts. These were compared with forecasts from traditional time-series approaches such as the naïve method (random walk without drift), exponential smoothing, Autoregressive Integrated Moving Average (ARIMA) and its spatiotemporal extension, STARIMA using the mean average error (MAE) accuracy evaluation statistic.

3.3 Spatiotemporal Hotspots and Coldspots

Snapshot approaches used to identify in which areas public confidence is improving or deteriorating over time do not adequately represent the underlying dynamics. We have applied a Bayesian mixture modeling approach developed by (Law, Quick, and Chan 2013) and expanded by (Li et al. 2014) to improve this. A two-stage classification is applied to the space-time interaction term so that areas can be identified as "hotspots", "coldspots" and "in between" which are getting "hotter", "cooler" or following the city-wide trend. An area is considered a hotspot, coldspot or in between based on the severity of the residual spatial trend i.e. a hotspot occurs if the spatial trend suggests it is very likely to be confident. Whether a neighborhood is getting hotter, cooler is determined by the slope of the local temporal trend when compared with the slope of the city-wide temporal trend.

4 Results

The PAS data was separated into a training set (April 2006 to March 2012; 24 quarters) for estimation and a testing set (April 2012 to March 2015; 12 quarters) for out of sample forecast evaluation. All of the data was then used for identifying hotspots and coldspots.

4.1 Spatiotemporal Estimation

Examining the spatial and temporal trend provides useful insight into the overall patterns. Figures 2 and 3 display the estimated spatial and temporal trends. For instance, rather than a clear "east/west divide" in a map of spatial confidence trends, we see that neighborhoods in south-west London are more likely to be confident in the police than the city-wide average. The empirical temporal trend (see Figure 1) is well captured by the temporal random effects.

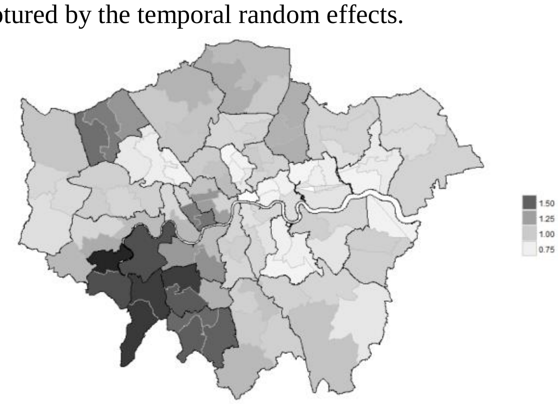

Figure 2: Map of the estimated spatial trend in confidence levels in London for the period April 2006- March 2012. Dark areas indicate higher confidence levels.

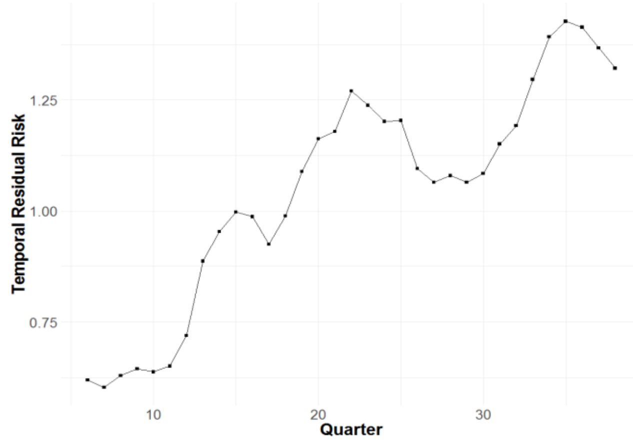

Figure 3: Time series plot of the estimated temporal trend in confidence levels in London for the period April 2006- March 2012.

4.2 Spatiotemporal Forecasting

One step ahead forecasts were obtained for 12 quarters (April 2012 – March 2015). Figure 4 shows the forecasts obtained for the city-wide level and also for the neighborhoods in the Borough of Camden.

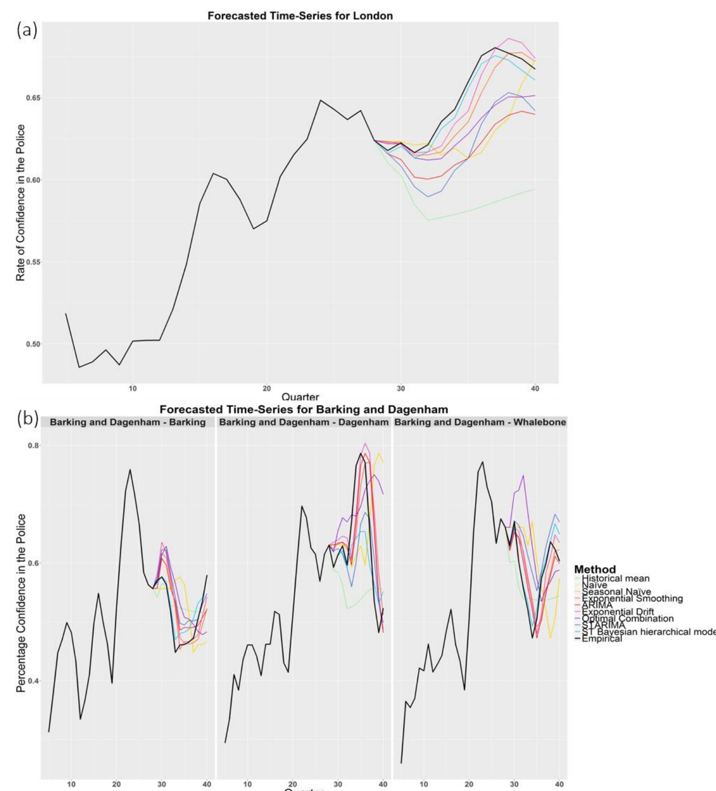

Figure 4: Public confidence per rolling quarter for London (above) and neighborhoods in the Borough of Camden from October 2006 to September 2013 with forecasts from April 2012

At first glance, it is apparent that the performance of the models varies considerably at the London-wide level, with the average/historical mean and seasonal naïve methods performing the worst overall. The spatiotemporal Bayesian hierarchical approach (shown in light blue) appears to be the best performing from a visual inspection. This is confirmed by the MAE statistics shown in Table 1 as our approach produced forecasts twice as accurate as the naive method.

Table 1: Forecast accuracy statistics

Method	MAE
Naïve (Random walk without drift)	0.04
Simple exponential smoothing	0.04
ARIMA	0.06
STARIMA (1,0,0)	0.06
ST Bayesian hierarchical modelling	**0.02**

4.3 Spatiotemporal Hot Spots and Coldspots

In our two stage classification, neighborhoods are first classified as hotspots, coldspots or neither. This classification can be seen in Figure 5 below. As expected, the "hotspots" of confidence in the police are mostly in the south-west with "coldspots" or areas of persistent low levels of confidence to the east.

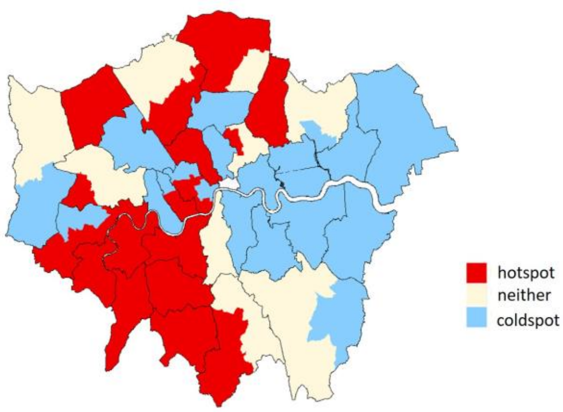

Figure 4: Map of the stage 1 classification. Neighborhoods have been classed as hotspots, coldspot of neither, with hotspots being very confident neighborhoods.

The neighborhood level trends are then further examined in the next stage of the classification. By comparing the local trend with the overall city-wide trend, neighborhoods are further classified as either getting hotter (increasing), cooler (decreasing) or neither (i.e. following the overall trend). Figure 5 visualizes this second stage classification for the neighborhoods which are hotspots. Some cause for concern are the hotspots which are getting cooler. These neighborhoods (shown in light pink), which typically have high rates of confidence, are getting less confidence at a rate faster than the overall city-wide rate. Policy makers can use this technique to identify areas which may need further attention or a more targeted intervention.

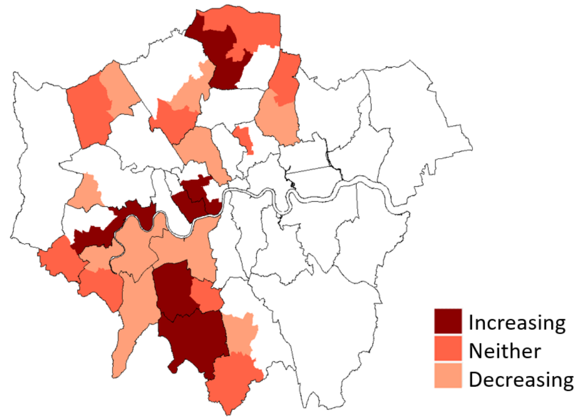

Figure 5: Map of the stage 2 classification for areas classed as hotspots. Very confident neighborhood (hotspots) have their trends compared with the London wide average. Neighborhoods classed as increasing are getting confident at a rate faster than the London average.

5 Discussion and Implications

This research explores the use of a Bayesian spatiotemporal approach to small area estimation for estimating, forecasting and classifying trends in public confidence in the police. The small area estimation approach enabled us to overcome the limitations of the sample size to provide intelligence at an operationally useful level. Combining the temporal dimension with the geography of public confidence allows us to move past a snapshot approach to provide a richer understanding of the patterns. Forecasts provide intelligence to inform proactive confidence interventions in neighborhoods. The two stage classification approach allowed neighborhoods to be labelled as hotspots, getting hotter or colder etc., and provides the specific neighborhood level statistical insight required for improving public confidence across neighborhoods. This research is relevant to all policy makers with spatiotemporal data who wish to boost the effective sample size of data to allow for analysis at finer levels of spatial aggregation. In this case, it is of specific interest to the Mayor's Office for Policing and Crime (MOPAC) as well as to the Neighborhood Boards responsible for engagement at the local level.

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