Key factors driving obesity in the UK

Michael C. A. Stevens[1], Yiqiao Chen[2], Alex Stringer[3], Caitlin Clemmow[4] and Lewis A. Jones[5]

[1]Department of Biological and Chemical Sciences, Queen Mary, University of London
[2]Department of Land Economy, University of Cambridge
[3]Department of Statistical Sciences, University of Toronto and Centre for Global Health Research, St. Michael's Hospital, Toronto
[4]Department of Crime Science, University College London
[5]Department of Earth Science and Engineering, Imperial College London

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Summary

Obesity is a persistent issue in the UK. Health Survey England has shown 64.3% of adults are classed as overweight. Research suggests areas where green space will positively impact obesity need to be identified. Here, we evaluate the importance of green space in comparison to other explanatory variables on obesity. We use a Generalised Linear Geostatistical Model to quantify any association between green space and obesity, accounting for demographic factors and unexplained spatial variation. We find the presence of green space is weakly associated with obesity, but mental health and unemployment are. We also identify geographic regions requiring intervention.

KEYWORDS: Spatial analysis, geostatistics, Bayesian modelling, greenspace, INLA.

1 Introduction

The World Health Organization (WHO) states that worldwide obesity has tripled since 1975 (World- Health-Organisation, 2018). The UK is no exception. In 2017, Health Survey for England (HSE) found that 64.3% of adults were classed from overweight to morbidly obese (Baker, 2019). Figure 1 illustrates obesity levels across the UK. A 2018 report from Fields in trust UK states 'we need a strategic approach to the provision of parks and green spaces by identifying areas where investment will have the most significant impact on individuals.' Fields In Trust UK also found that green spaces are estimated to save the National Health Service (NHS) £111 million/year by reducing the number of GP visits and subsequent prescriptions and referrals (Fields-In-Trust, 2018). Despite this, a variety of studies have found that there is a positive, but weak association between a reduction in obesity and availability of green spaces and sports facilities (Bedimo-Rung, 2005; Lachowycz and Jones, 2011; Lee and Maheswaran, 2011; Huang et al., 2015; Jean-louis, 2018). Against this background, we intend to answer the following questions: 1) Whether the availability of green spaces and sport facilities are associated with the obesity rate in England, 2) What are other demographic factors driving obesity in England, and 3)Which districts in England should be prioritised for targeted intervention against obesity? In order to answer the questions, we investigate the

[1] M.Stevens@qmul.ac.uk
[2] YC418@cam.ac.uk
[3] Alex.Stringer@mail.utoronto.ca
[4] C.Clemmow.17@ucl.ac.uk
[5] L.Jones16@imperial.ac.uk

spatial distribution of obesity in England. We first evaluate the importance of green spaces and sports facilities in tackling obesity and then assess the significance of other potential explanatory variables. Finally, we identify the districts that can be prioritised for targeted intervention against obesity according to our modelling results. This research will also contribute to the UK government's industrial strategy grand challenge: "Use data, Artificial Intelligence and innovation to transform the prevention, early diagnosis and treatment of chronic diseases by 2030," as set out in its 2017 industrial strategy.

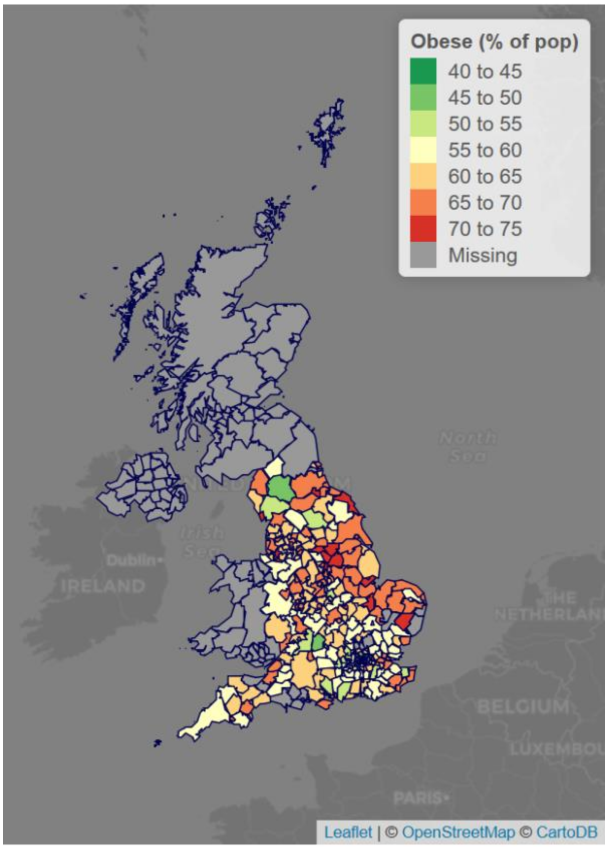

Figure 1: The percentage of population obesity at local authority district-level from Public Health England

2 Methods

2.1 Data

We accessed data from Public Health England via the R package fingertipsR (R Core Team, 2019; Fox and Flowers, 2019). The predictors available to us for the period 2017-18 were: % of obese or overweight adults, population, number of green spaces, sports facilities, % of adults walking or cycling for travel at least three days a week, % of overcrowded households, number of premises licensed to sell alcohol per km^2, density of fast food outlets, unemployment rates, prevalence of common mental disorders (% aged 16 and above), adults with low education (% aged 16 and over) and average weekly earnings. We used the finest scale available to us (local authority district (LAD) level) whilst also conforming to the NHS's requirement of anonymity.

2.2 Model

We use a Besag, York and Mollie (BYM) model (Besag et al., 1991; Brown, 2015) to quantify any association between obesity rates and our demographic variables, including the presence of greenspaces. The model accounts for spatial heterogeneity in obesity rates, and provides estimates both of the expected obesity rates, and the spatially smoothed excess obesity rates for each LAD. The latter can be used to identify specific LADs with higher-than-expected obesity rates, which can be used to target policy interventions. Let Y_i be the count of the number of obese persons and E_i the population of LAD i. Let λ_i be the obesity rate of LAD i, so that the expected number of obese individuals is $E(Y_i) = E_i\lambda_i$. We model $Y_i \sim$ Poisson ($E_i\lambda_i$), and model the obesity rate through a log-linear relationship with the covariates. The model was implemented using the geostatsp and diseasemapping R packages (Brown and Zhou, 2018; Brown, 2019).

$$
\begin{aligned}
Y_i &\overset{ind}{\sim} \text{Poisson}\left(P_i\lambda_i\right), i = 1, \ldots, n && \text{Number of obese people } Y_i \text{ and people } P_i \text{ in LSOA } i \\
\log \lambda_i &= \mu + \boldsymbol{X}_i\boldsymbol{\beta} + U_i + V_i && \text{log-risk of obesity} \\
U_i &\sim \text{Normal}\left(0, \Sigma_U\right) && \text{Spatially structured variation} \\
V_i &\sim \text{Normal}\left(0, \sigma_v^2 I\right) && \text{Unstructured variation}
\end{aligned}
$$

3 Results

Results from the model can be seen in Figure 2. Table 1 illustrates the contribution of each predictor on obesity levels. Of the chosen predictors, mental health was most strongly associated with obesity levels, while green space and sports facilities made low contributions. Table 2 outlines those districts with the highest excess obesity. These districts should be investigated further, as there may be unidentified risk factors present, the identification of which could lead to policy intervention. Being able to identify specific regions of excess obesity significantly reduces the cost and effort of intervention and is a major advantage of our approach.

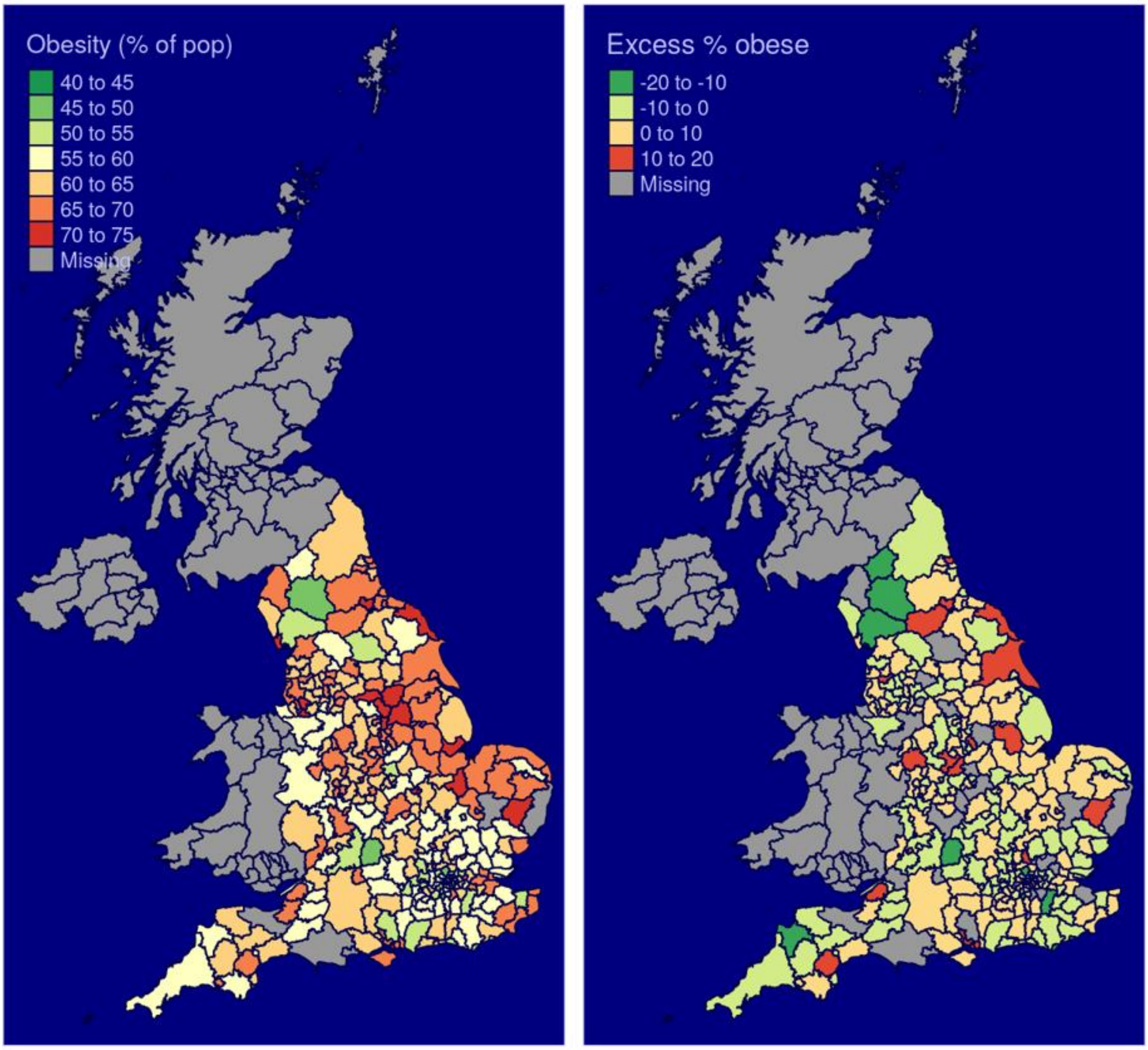

Figure 2: Obesity and excess obesity levels at local authority district-level fitted by the generalised linear geostatistical model

Table 1: Results from the model - predictors of obesity used in the model and their association with obesity

Variable	Association with obesity
Greenspaces	0.00%
Sport facilities	-0.01%
Alcohol	-0.18%
Cycling	-0.18%
Fast food density	-0.03%
Low education	0.53%
Mental Health	0.97%
Overcrowded households	-0.52%
unemployment	0.72%
Walking	-0.08%

Table 2: UK districts with the highest excess obesity levels

District	Excess obesity
Gosport	16.00%
Fareham	15.70%

Mid Suffolk	14.55%
Eastleigh	13.46%
South Ribble	12.82%

4 Discussion and Conclusion

We assessed the importance of green spaces and sport facilities in managing obesity. Our result show that the presence of green spaces or sport facilities is weakly associated with obesity while mental health, unemployment and overcrowded households level have stronger associations with the obesity rate in each local authority district. Thus, policymakers could pay more attention to the improvements of mental health issues, unemployment, and household conditions in tackling obesity. Besides, our modelling results also found the geographic regions that require interventions as they have worse performance after accounting social-demographic factors and unexplained spatial variation. The geographic regions requiring interventions are Gosport, Fareham Mid Suffolk, Eastleigh and South Ribble.
The effectiveness of measures to tackle obesity, at a population level, is limited and a whole system approach is costly in a climate of limited resources. We believe that geographically targeted interventions should be implemented to identify areas most in need and those most likely to result in the greatest reward. This approach also enables local authorities to take ownership of a problem affecting their district. The model highlights mental health and education as the factors requiring intervention in reducing obesity. Further investigation is required into how these explanatory variables are linked and which cost effective interventions can target all associated predictors as opposed to targeting them individually. A caveat, however, is that long-term investment and time-consuming measures are required to evaluate the effectiveness of any intervention that could be used to assess the model. Although we identified the potential areas that need intervention, the policy recommendation was made without the reinforcement of health inequalities. Data quality is a tentative subject when investigating public health data; although point pattern data may be ideal for the model, spatially aggregated data is required to meet ethical standards.

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Biography:
Michael Stevens: Michael is a final year PhD student working on geographic profiling; a spatial model originally developed in criminology, but he applies it to different cases within ecology and disease. His specific interests lie in Bayesian MCMC algorithms and their applications.
Yiqiao Chen: Yiqiao is a second-year PhD candidate in Land Economy at the University of Cambridge. She works on dynamic urban modelling and smart city policies.
Alex Stringer: Alex is a second-year PhD candidate in Statistics at the University of Toronto supervised by Patrick Brown and Jamie Stafford. He is developing a

methodology that has applications in global mortality research and disease mapping, and also works at the Centre for Global Health Research at St. Michael's Hospital in Toronto.
Caitlin Clemmow: Caitlin is a final year PhD student working on detecting dynamic behavioural patterns and configurations of risk factors in a range of targeted violence offenders including terrorists, mass murderers and the pathologically fixated, to improve the threat and risk assessment of offenders in this space.
Lewis Jones: Lewis is a final year Palaeobiology PhD student. He uses spatial analyses to improve understanding of the spatial structure of life in the past, and the fossil record.

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