Modelling the health impacts of an extreme event in an urban area

October 2020

Katty Huang, Andrew Charlton-Perez, Ting Sun

University of Reading

Contents

The UK Climate Resilience programme is supported by the UKRI Strategic Priorities Fund. The programme is co-delivered by the Met Office and NERC on behalf of UKRI partners AHRC, EPSRC, ESRC.

Activity 3:
Modelling the health impacts of an extreme event in an urban area

By: Katty Huang, Andrew Charlton-Perez, Ting Sun

Summary

Emergency hospital admissions in London boroughs are analysed for their relationship with temperature exposure. To capture variations to exposure in an urban setting, the ambient temperature is modelled using the SUEWS urban model. Boroughs that are typically warmer than average in winter are found to have lower daily admission rates than average. However, our study does not prove a causal relationship, and as the average difference in admissions does not vary with season, no correlations can be noted in summer.

To delve specifically into temperature-related admissions, a distributed lag non-linear model is used to estimate the exposure-response relationship for London as a whole and applied to each borough. We focus on two extreme events in 2018 as case studies: a heatwave near the end of July and a cold spell at the end of February. The maximum temperature difference between boroughs averages to around 1°C during the heatwave and 2°C during the cold spell. With additional differences in background admissions between boroughs, this translates to a maximum of 44% difference in temperature-related admissions between boroughs during the heatwave and a maximum of 71% difference during the cold spell. The magnitude of the attributed admissions and their differences, however, is small, and given the significant uncertainties associated with the exposure-response model, attributed admissions for each borough lie within each other's 95% confidence interval range, particularly during the heatwave.

Two aspects determine the difference in the temperature-attributed admissions between boroughs: the difference in temperature, and the difference in the admissions counts. Controlling for the difference in background admissions between boroughs reveals that the role of temperature difference between boroughs is small in contributing to differences in attributed admissions. The interquartile range of attributed admissions across boroughs during the heatwave/cold spell reduces by 80%/84% when background admission variability is excluded.

To explore the source of other underlying factors which contribute to differences in hospital admissions across boroughs, average admissions and attributed admissions during the heatwave/cold spell are compared to various measures socioeconomic, environmental, and demographic conditions. No clear, singular factor can be identified that explains the difference in hospital admissions between the boroughs, and in some cases, the direction of statistically significant correlations is opposite to what may be expected. For instance, higher green space fraction, especially in the form of grass cover, is consistently correlated with higher hospital admissions, particularly in Inner London boroughs. This is indicative of possible confounding factors not considered in the parameter space and reveals some of the complexities in attributing variations in hospital admissions.

Overall, the results of this study indicate that the difference in temperature at borough levels play a small role in controlling the difference in their attributed hospital admissions. For the purpose of climate services, it should be noted that more complicated societal and environmental factors may have a much stronger influence on the variation in admission counts on the borough scale, even when urban microclimate impacts on ambient temperature variation are considered.

Data

Emergency hospital admissions accumulated to London borough levels are obtained from the Met Office, available from April 1997 to end of March 2019. An overall steady increase in hospital admissions can be noted over this time period, partly related to the increase in population, though this does not account for a sharp increase in admissions between approximately 2003 and 2005 and recently from around 2017 (*Figure 1*). Daily admission counts of less than 6 in a borough are not available due to privacy restrictions. As such, the admission data is usable, with sufficient counts, from around April 1999.

The change in admissions over time is not uniform across boroughs. The greatest population-normalised increase in admissions after 2005 are found in the outer boroughs, especially to the west and south-west (*Figure 2*a). The trend continues after 2005, with increases in the outer boroughs and decreases in the inner boroughs when comparing between the 2005-2009 average and the 2010-2019 average (*Figure 2*b). Given this shift in admissions pattern between boroughs, admissions averaged over the most recent decade is used for correlation analyses with socioeconomic, environmental, and demographic parameters, which are all based on conditions in more recent years.

Yearly borough population data for normalising the admissions is obtained from the London Datastore (https://data.london.gov.uk/dataset/land-area-and-population-density-ward-and-borough). Population data up to year 2010 are from the Office for National Statistics' Mid-year Estimates, and from 2011, are Greater London Authority's 2016-based projections.

For attribution of hospital admissions associated with temperature exposure, temperature-lag-admissions relationship is estimated using a Distributed Lag Non-linear Model for London as a whole. Optimal statistical fit is obtained by minimising the quasi-Akaike information criterion (QAIC) while restricting the background regression for temporal/seasonal trends to 8 degrees of freedom per year and allowing for up to three knots in the temperature dimension. The optimal fit considers 28 lag days, with 3 logarithmically-spaced knots in the lag dimension, and temperature knots at the 0.4 and 0.9 quantiles (*Figure 3*).

Borough-level temperature data at 2 m above ground level are modelled using the Surface Urban Energy and Water Balance Scheme (SUEWS) urban climate model, driven by ERA5 reanalysis data, run at Lower Super Output Area (LSOA) grids and cumulated to borough levels, from October 2015 to the end of 2019.

For other factors, the Indices of Deprivation 2019 dataset, based mainly on 2015/2016 data is used (https://www.gov.uk/government/collections/english-indices-of-deprivation). Individual deprivation indices are available for measuring relative deprivation in income, employment, education, health, crime, barriers to housing and services, and living environment, and for quantifying an index of multiple deprivation (IMD) which contains a weighted combination of the above-listed deprivation domains. Additionally, the landcover fractions of trees and grass from SUEWS' model input are used for analysing the relation of admissions to green space.

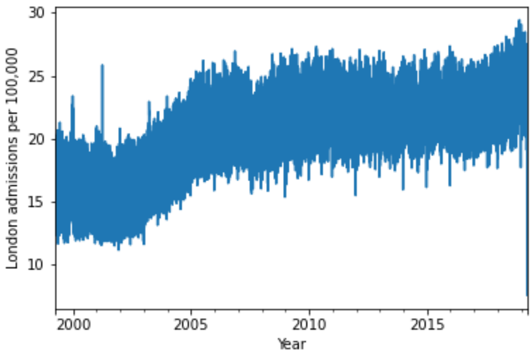


Figure 1: Emergency hospital admissions per 100,000 people across all London boroughs from April 1999 to March 2019.

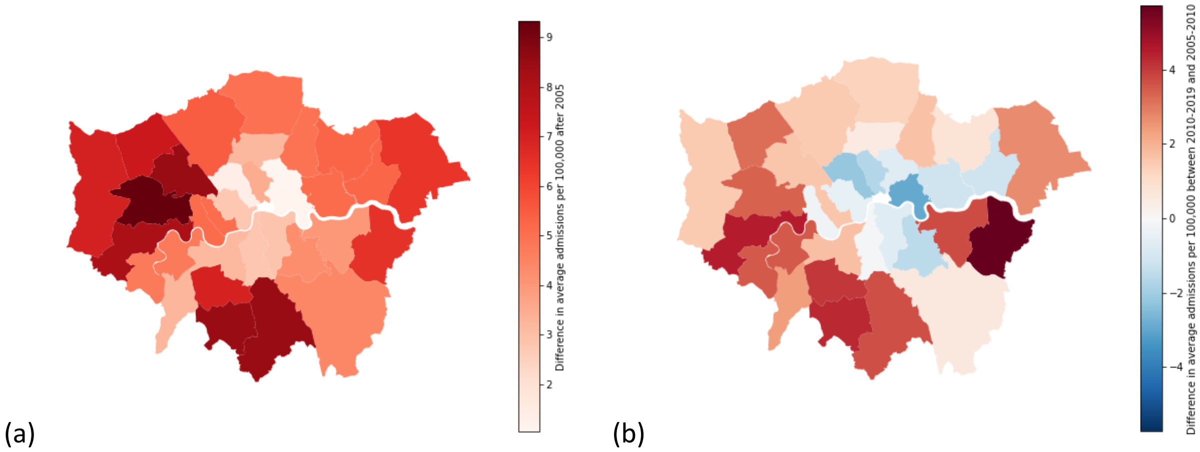


Figure 2: Change in admissions per 100,000, at borough levels, with (a) the average after 2005 compared to the average before, and (b) the 2010-2019 average compared to the 2005-2009 average.

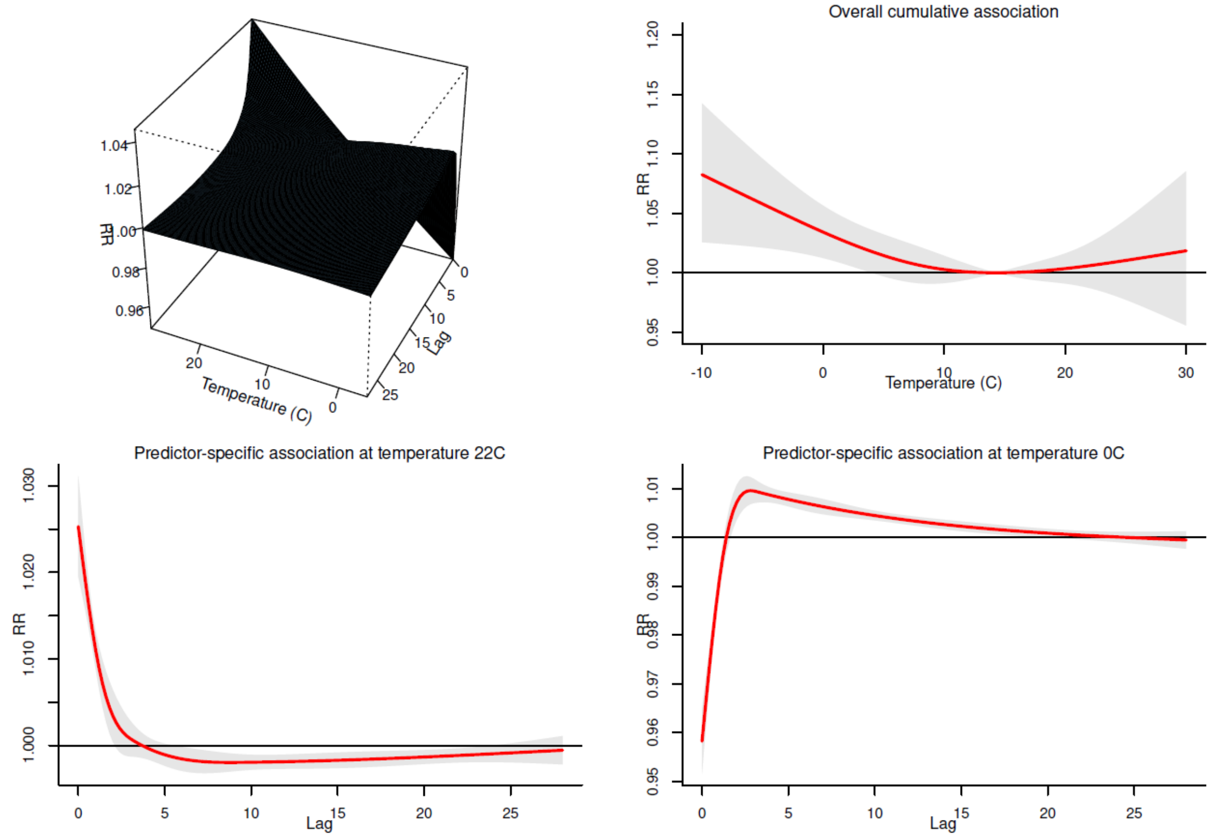


Figure 3: Temperature-admissions exposure-response model for London.

Data availability

The following data are available from the current analysis:

- Temperature-lag-admissions model for London as a whole
- SUEWS simulated daily mean temperatures for each London borough between October 2015 and December 2019 (however, it should be noted that the SUEWS model setup at LSOA grids is experimental)
- Time series of the attributed admissions at borough levels from October 2015 to December 2019, using the above admissions model and SUEWS simulated daily mean temperatures

Should it be desirable, the analyses described in this report can also be repeated for mortality instead of admissions data. A concern with such an analysis is that one may often reach the limit of too few daily mortality counts at borough levels.

A temperature-lag-mortality model has also been fitted for the Greater Glasgow and Clyde health board, and SUEWS simulation of daily mean temperatures is available for Glasgow. Given the findings for London, however, no further analyses are currently performed for Glasgow. This may be added (though with less detail due to lack of mortality data for sub-health board regions) if needed.

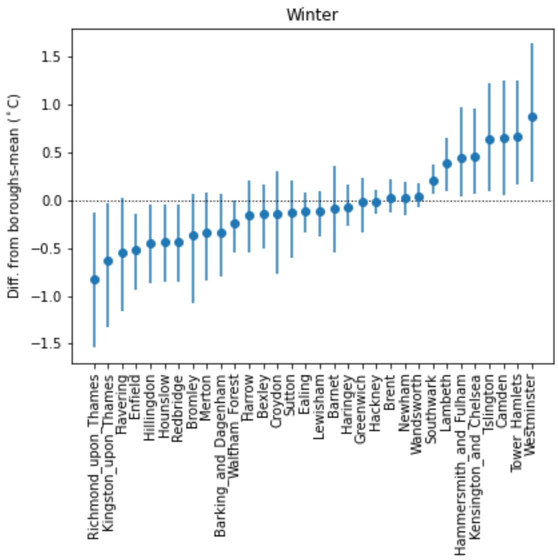
Do colder/warmer boroughs have higher/lower hospital admissions?

To investigate if certain boroughs are consistently colder or warmer than others, and if there is a corresponding difference in average hospital admissions, analyses are performed on the daily borough difference from the boroughs-mean temperature and admissions per 100,000. This removes trends and fluctuations associated with large scale factors that impact the entire region and focuses on the relative difference between boroughs within Greater London.

During winter, Inner London boroughs tend to be consistently (at least 95% of days) warmer than average, while boroughs in the southwest and northeast tend to be consistently colder (*Figure 4*). Difference across boroughs is less pronounced and less consistent in summer (*Figure 5*). Most boroughs fluctuate between being cooler or warmer than the boroughs-average. On average between 2016 and 2019, however, boroughs in eastern London tend to be warmer while those to the north and to the south tend to be cooler in summer (*Figure 5*b).

Applying the same analysis to emergency hospital admissions yielded a similar level of variability for the boroughs as temperatures in summer. At the 95% level, most boroughs have both days when their hospital admission rates are higher than the average and days when it is lower (*Figure 6*a, *Figure 7*a). However, the average difference from the mean is not found to depend on the season (*Figure 6*b, *Figure 7*b). In general, Inner London boroughs have lower hospital admissions per 100,000 than Outer London boroughs in both winter and summer.

When comparing each borough's mean temperature and hospital admission deviation from the daily boroughs-average, statistically significant (p-value of 0.00005) negative correlation can be noted in winter, with a correlation coefficient of -0.65 (for both Pearson's and Spearman's correlation). This indicates that boroughs which are warmer in winter also have lower hospital admission rates than average. Given that the admissions pattern does not vary with season, however, it is possible that the correlation reflects the influence of other confounders. Correlation between the two variables is not statistically significant in summer.



(a) (b)

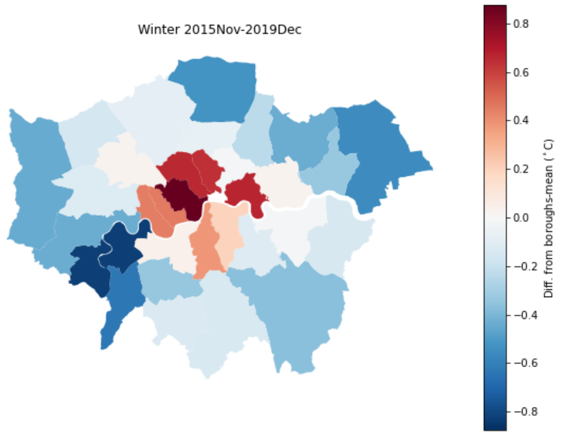
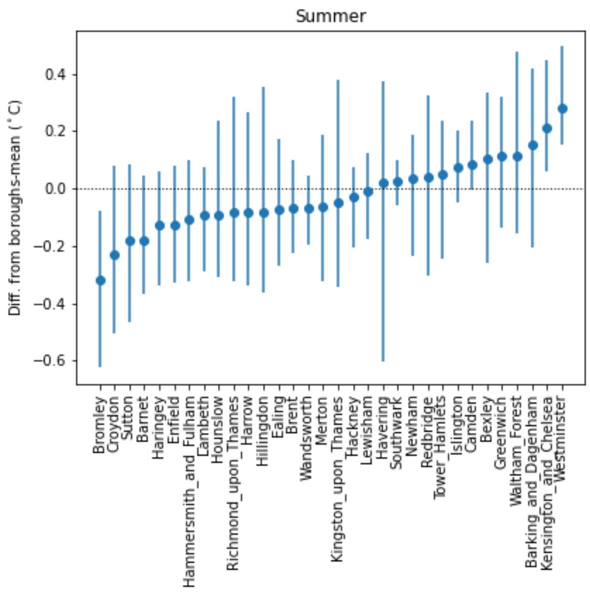


Figure 4: The difference in borough daily mean temperature from the daily boroughs-average (a) averaged for winter months (NDJFM), with 95% interval based on SUEWS modelled data from 2015 November to end of 2019, ordered from coldest to warmest boroughs. Borough averages are additionally mapped in panel (b).



(a)

(b)

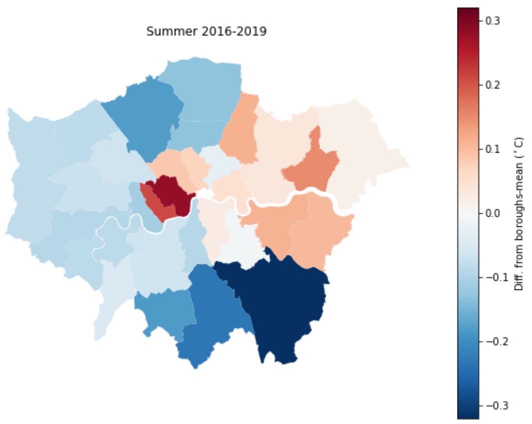
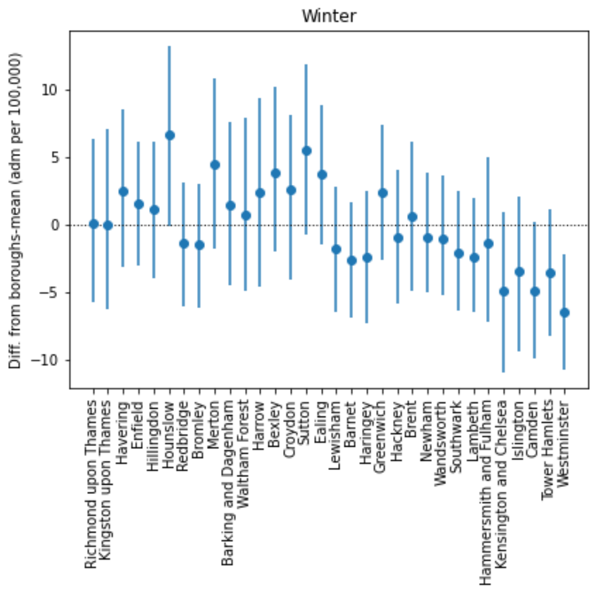


Figure 5: As Figure 4 but for summer (JJA) 2016 to 2019 and with boroughs in panel (a) ordered by the summer mean temperature deviation from the boroughs-average.



(a)

(b)

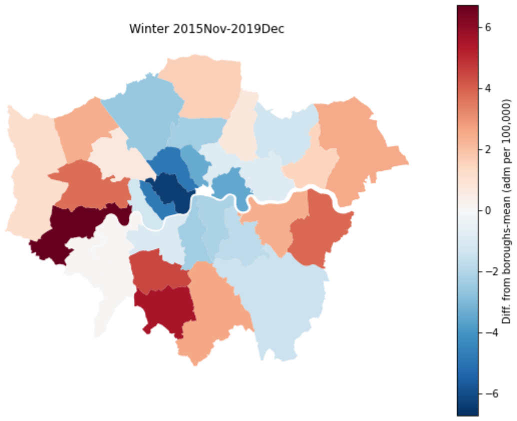
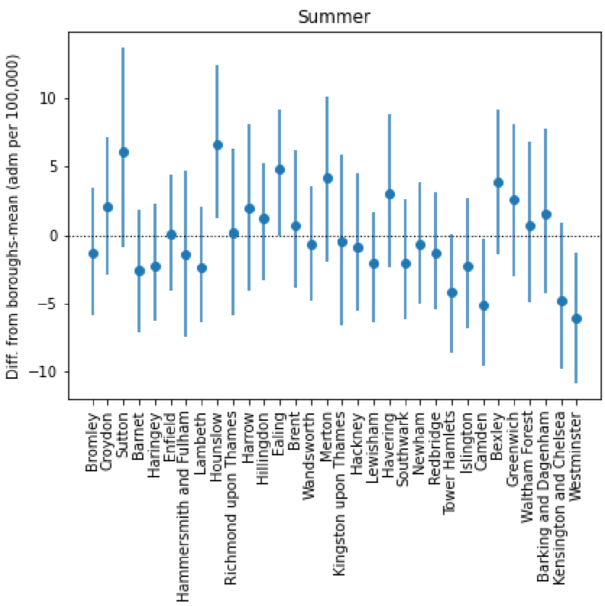


Figure 6: As Figure 4 but for hospital admissions per 100,000. Boroughs in panel (a) are ordered according to Figure 4a, from coldest to warmest.



(a) (b)

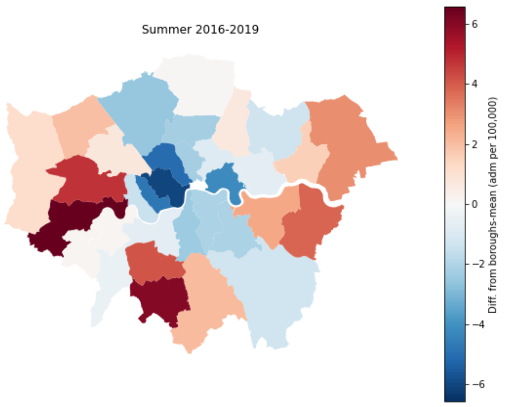


Figure 7: As Figure 5 but for hospital admissions per 100,000. Boroughs in panel (a) are ordered according to Figure 5a, from coldest to warmest.

2018 heatwave and cold spell events

Two extreme events in 2018 are examined: a heatwave from 22nd to 27th of July and a cold spell from February 22nd to March 3rd. To calculate the hospital admissions attributable to temperature, the temperature-admissions relationship for London as a whole (*Figure 3*) is applied to all boroughs.

Averaged over the heatwave period, the maximum temperature difference between boroughs is 0.9°C, with highest temperatures in Inner London and boroughs to the northeast. Given the shallow slope of the cumulative temperature-admissions relationship at warm temperatures (*Figure 3*), this translates to a cumulative attributable fraction difference between boroughs of up to 0.08%. The maximum difference in cumulative temperature-attributed admissions between boroughs is 0.08 per 100,000, out of an average attributed admission of 0.18 per 100,000 (44% difference). Averaged over the cold spell period, the maximum temperature difference between boroughs is up to 2°C, translating to 1%

difference in attributable fraction, and up to 0.7 per 100,000 in attributable admissions out of an average of 0.99 per 100,000 (71% difference).

How important is temperature compared to other factors in determining the variation in hospital admissions between boroughs?

While the attributable fraction varies purely with temperature (since the exposure-response relationship is identical for all boroughs in this case), the cumulative attributable admission is calculated by multiplying the attributable fraction by the average admissions over the lag period. The latter therefore additionally includes variations in admissions between boroughs that are attributable to socioeconomic, population age, or other factors. To separately quantify the role of temperature variation across boroughs in their hospital admission differences, an additional analysis is performed by multiplying the attributable fraction by a constant admission averaged across all boroughs during the event and subsequent lag period (*Figure 8*a,c, *Figure 9*a,c). When controlling for all other factors aside from temperature as such, the maximum difference in attributable admissions between boroughs is 0.2 per 100,000 during the cold spell and 0.03 per 100,000 during the heatwave. This contrasts with differences of up to 0.6 per 100,000 during the cold spell and up to 0.09 per 100,000 during the heatwave when differences in admissions due to other factors are included (*Figure 8*b,d, *Figure 9*b,d). The interquartile range of attributed admissions reduces by 80%/84% during the heatwave/cold spell when controlling for non-temperature factors.

Additionally, it should be noted that given the significant uncertainty in the temperature-admissions model, the shallow slope of this exposure-response relationship, and the relatively small temperature difference between boroughs, most boroughs have overlapping confidence intervals in their attributed admissions/fractions (*Figure 8*c,d*Figure 9*c,d). This is particularly true for the heatwave (*Figure 9*) and when variations due to non-temperature-related factors are excluded (*Figure 8*c).

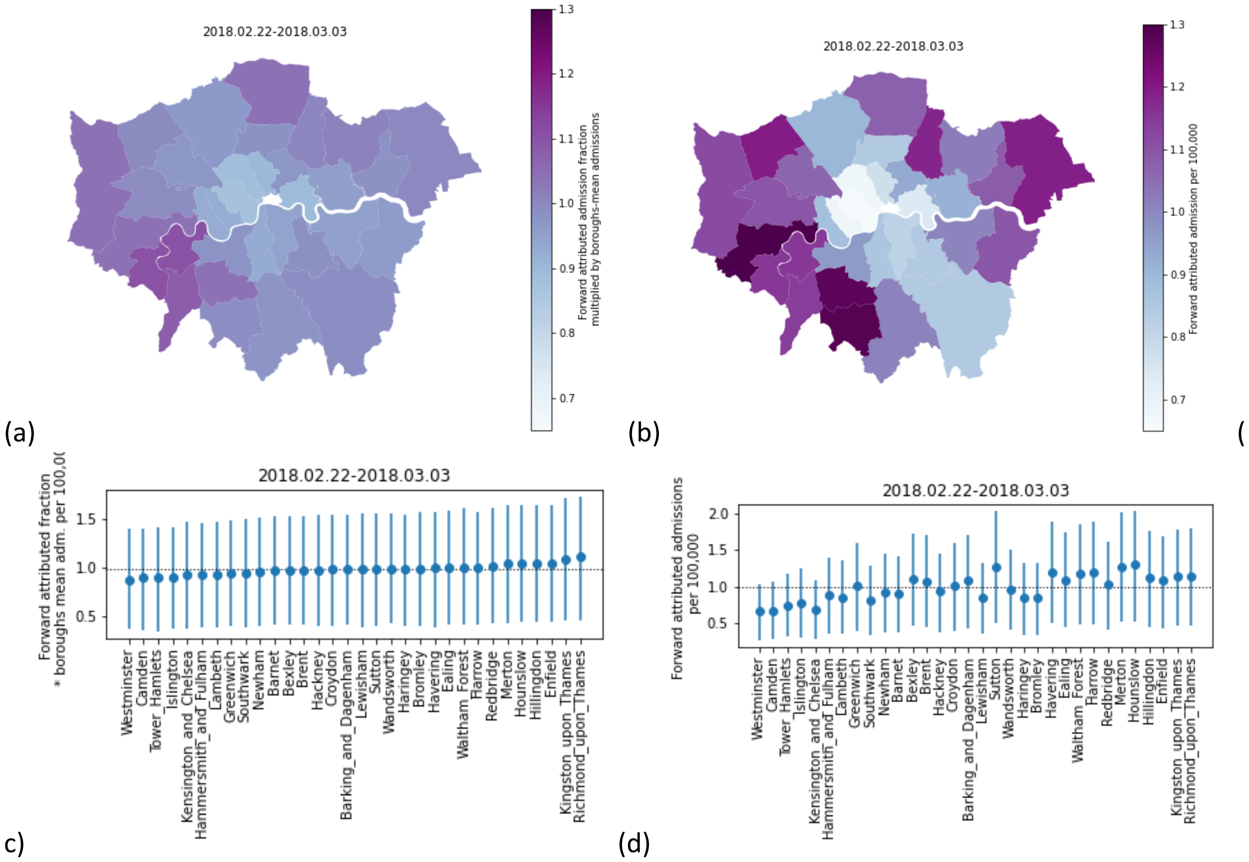


Figure 8: Forward attributed admissions calculated by multiplying the forward attributed fraction by (a) a constant average admissions across all boroughs during the entire event and lag period, and (b) the actual average admission for each borough during the event and lag period. Panels (c) and (d) show the respective 95% confidence intervals based on 5000 Monte Carlo simulations, with boroughs ordered from warmest to coldest.

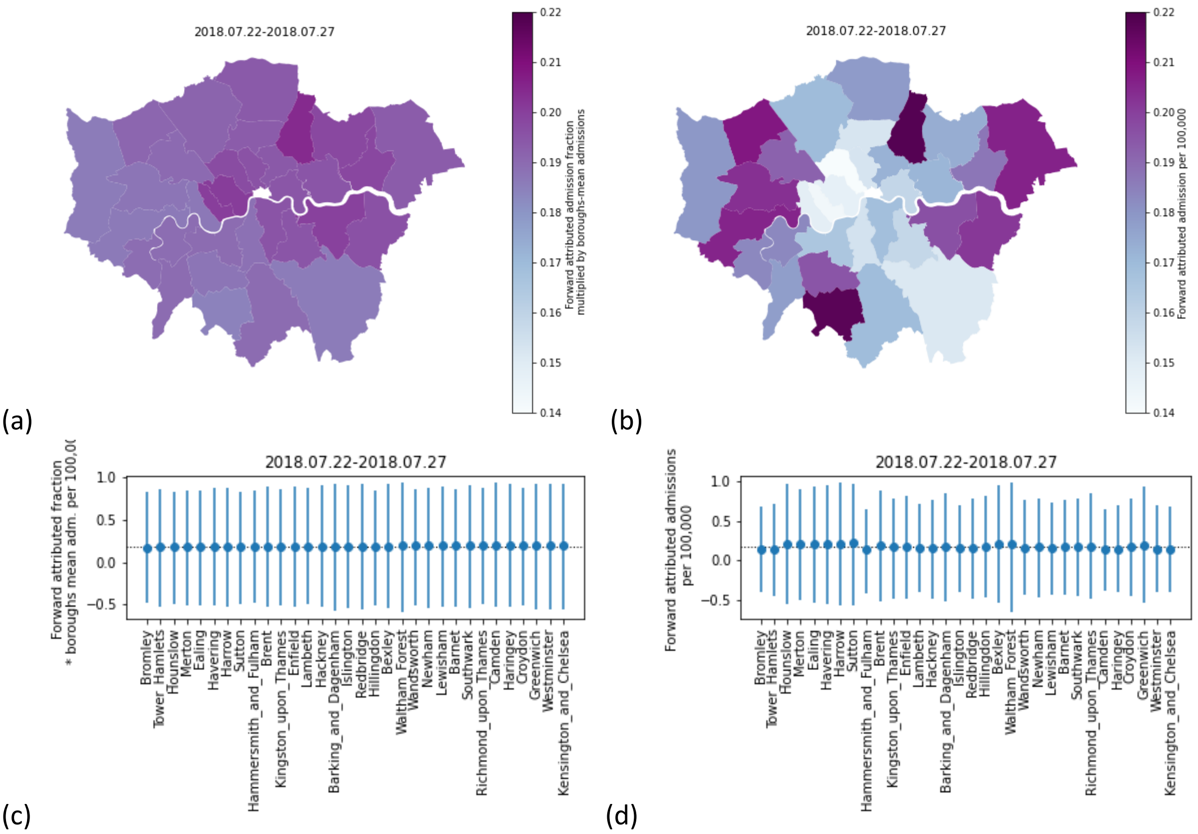

(a) (b) (c) (d)

Figure 9: As Figure 8 but for the 2018 heatwave and with boroughs in panels (c) and (d) ordered from coolest to warmest.

Correlation with other factors

To examine which other factors may be contributing to the variation in hospital admissions across boroughs, correlation analyses are performed between admissions and various socioeconomic, environmental, and demographic measures (*Table 1*). Overall, the number of hospital admissions (the overall average in the recent decade and the temperature-attributed admissions during the 2018 heat and cold events) is correlated (95% significance level) with the environmental condition, including the fraction of green space and the living environment deprivation index, which includes both indoor (housing condition) and outdoor (air quality, traffic accident danger for pedestrians) conditions. However, the sign of the correlation is not as expected. Boroughs with more deprived living environments tend to have lower average admissions, and those with greater fractions of green space tend to have greater admissions. An exception is the fraction of deciduous trees, which is negatively correlated with admissions, though this correlation is only statistically significant for the 2010-2019 average. Deprivations in income, employment, and crime conditions are also found to be correlated with lower attributed admission during the 2018 cold spell. Lastly, correlations which align with expectations in sign are found between the 2010 to 2019 average admissions and education/skills/training deprivation, and between the 2018 cold spell average attributed admissions and the proportion of population over 65 years of age, who are more susceptible to extreme temperatures.

The unexpected sign of the correlation coefficients indicates possible confounders aside from the parameters examined. Both event-average temperature attributed admissions (*Figure 8*b, *Figure 9*b) and overall average admissions between 2010 and 2019 (*Figure 10*) show fewer population-normalised admission counts in Inner London boroughs, while these boroughs tend to be more deprived and have lower green space coverage. To remove some of this difference which may be attributed to other factors, correlations are also analysed separately for inner and outer London boroughs (*Table 2*, *Table 3*). For Inner London, greater grass coverage in the borough continues to be correlated with higher hospital admissions. However, during the 2018 heatwave event, health deprivation and barriers to housing and services are correlated with higher attributed admissions, while having a greater proportion of the population being over 65 is correlated with lower temperature-associated hospital admissions. Few correlations are found for the Outer London boroughs. There, the decade-average admissions are correlated with health and education deprivations, while attributed admissions during the heatwave is negatively correlated with the vegetated fraction.

Overall, it is difficult to pinpoint the societal or environmental factors controlling the differences in hospital admissions across boroughs. Expected factors such as health deprivation or population age do not appear to be consistent predictors of high admissions, and correlations with the housing/heating condition, included in the living environment deprivation measure, are either of the wrong sign or not statistically significant. Relatively rapid changes in societal/environmentl conditions, which may not be well captured in the data, and low signal-to-noise ratios at such fine resolutions, may have also contributed to difficulties in disentangling the roles of different factors.

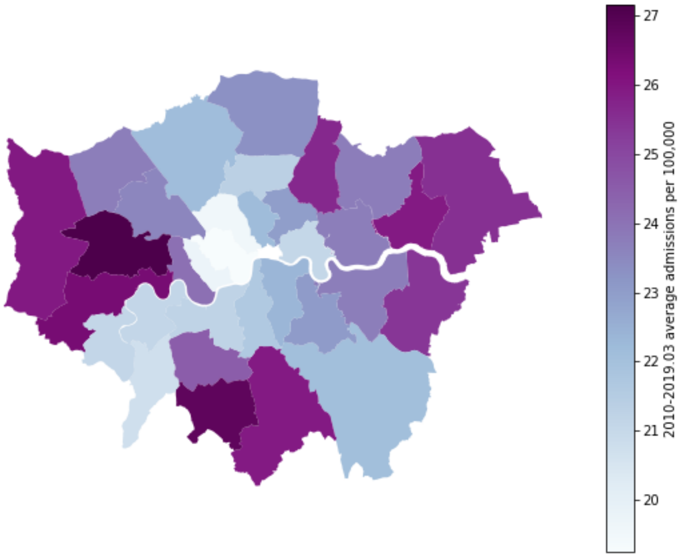


Figure 10: Average emergency hospital admissions per 100,000 from 2010 January to 2019 March.

Table 1: Spearman's ranked correlation coefficient and p-value for correlations between average admissions and various socioeconomic or environmental factors. Note that for all deprivation measures, the index scores are used, with higher scores indicating greater deprivation. The index of multiple deprivation is a weighted combination of deprivation scores in income, employment, education, health, crime, barriers to housing and services, and living environment. The vegetated fraction is the sum of spatial coverage from all three vegetation types (evergreen, deciduous, and grass), which are used as inputs for the SUEWS model. Correlations significant at the 95% level are highlighted in bold.

	2010-2019 March average admissions per 100,000		2018 heatwave average attributed admissions per 100,000		2018 cold spell average attributed admissions per 100,000	
	r_s	p-value	r_s	p-value	r_s	p-value
Index of multiple deprivation	0.02	0.91	-0.24	0.19	**-0.41**	**0.02**
- Health deprivation	0.2	0.28	-0.12	0.52	-0.25	0.16
- Living environment deprivation	**-0.41**	**0.02**	**-0.57**	**0.0007**	**-0.60**	**0.0003**
- Barriers to housing and services	0.27	0.14	0.13	0.48	-0.02	0.92
- Income deprivation	-0.03	0.89	-0.26	0.16	**-0.43**	**0.01**
- Employment deprivation	0.03	0.87	-0.24	0.18	**-0.43**	**0.01**
- Crime	-0.05	0.80	-0.30	0.09	**-0.44**	**0.01**
- Education, skills, and training deprivation	**0.50**	**0.003**	0.33	0.06	0.17	0.34
Vegetated fraction	**0.37**	**0.04**	**0.54**	**0.001**	**0.63**	**0.0001**
- Evergreen fraction	**0.34**	**0.05**	**0.36**	**0.04**	**0.43**	**0.01**
- Deciduous fraction	**-0.36**	**0.05**	-0.16	0.37	-0.10	0.60
- Grass fraction	**0.55**	**0.001**	**0.63**	**0.0001**	**0.70**	**0.000008**
Proportion of population above 65	0.15	0.42	0.30	0.09	**0.41**	**0.02**

Table 2: As Table 1 but for Inner London boroughs only.

	2010-2019 March average admissions per 100,000		2018 heatwave average attributed admissions per 100,000		2018 cold spell average attributed admissions per 100,000	
	r_s	p-value	r_s	p-value	r_s	p-value
Index of multiple deprivation	0.53	0.06	**0.62**	**0.02**	0.39	0.19
- Health deprivation	0.52	0.07	**0.54**	**0.05**	0.33	0.27
- Living environment deprivation	-0.12	0.71	-0.28	0.35	-0.27	0.36
- Barriers to housing and services	0.49	0.09	**0.59**	**0.03**	0.44	0.13

- Income deprivation	0.42	0.15	0.5	0.08	0.23	0.45
- Employment deprivation	0.50	0.08	0.41	0.16	0.21	0.49
- Crime	0.41	0.17	0.45	0.12	0.40	0.17
- Education, skills, and training deprivation	0.35	0.24	0.56	0.05	0.26	0.39
Vegetated fraction	0.35	0.24	**0.57**	**0.04**	**0.68**	**0.01**
- Evergreen fraction	0.24	0.44	0.15	0.62	0.21	0.49
- Deciduous fraction	-0.53	0.06	-0.54	0.06	-0.53	0.06
- Grass fraction	**0.68**	**0.01**	**0.76**	**0.002**	**0.78**	**0.002**
Proportion of population above 65	-0.46	0.11	**-0.71**	**0.006**	-0.45	0.12

Table 3: As Table 1 but for Outer London boroughs only.

	2010-2019 March average admissions per 100,000		2018 heatwave average attributed admissions per 100,000		2018 cold spell average attributed admissions per 100,000	
	r_s	p-value	r_s	p-value	r_s	p-value
Index of multiple deprivation	0.37	0.12	0.07	0.76	-0.27	0.26
- Health deprivation	**0.64**	**0.003**	0.28	0.25	-0.04	0.87
- Living environment deprivation	0.26	0.28	0.20	0.42	0.19	0.43
- Barriers to housing and services	0.26	0.29	0.04	0.86	-0.26	0.28
- Income deprivation	0.33	0.16	0.06	0.81	-0.30	0.22
- Employment deprivation	0.38	0.11	0.09	0.70	-0.31	0.19
- Crime	0.33	0.17	-0.02	0.95	-0.33	0.16
- Education, skills, and training deprivation	**0.49**	**0.03**	0.20	0.41	-0.08	0.75
Vegetated fraction	-0.41	0.08	**-0.46**	**0.05**	-0.18	0.46
- Evergreen fraction	-0.16	0.50	-0.33	0.16	-0.21	0.39
- Deciduous fraction	-0.44	0.06	-0.29	0.23	-0.17	0.48
- Grass fraction	-0.04	0.87	-0.24	0.33	-0.02	0.95
Proportion of population above 65	-0.30	0.21	-0.13	0.59	0.03	0.90

Met Office
FitzRoy Road, Exeter
Devon EX1 3PB
United Kingdom

Tel (UK): 0370 900 0100 (Int) : +44 330 135 0000
Fax (UK): 0370 900 5050 (Int) :+44 330 135 0050
enquiries@metoffice.gov.uk
www.metoffice.gov.uk