COVID-19 Lockdowns' Impact on Crime in London
(Working Paper)

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Summary

The study tried to depict the spatio-temporal change of crime in London over the pandemic from March 2020 to December 2020, complemented by the analyses on confirmed coronavirus cases and mobility change by London boroughs and land use types during the target period respectively. Temporally, three national milestone periods (23rd March to 10th May, 3rd August to 31st August and 31st October to 2nd December) had been selected as benchmark to evaluate the crime-deterrent or criminogenic effects from either lockdown or Eat-Out policies. Upon identifying (1) the most changed crime types affected by the pandemic geographically; (2) the most influenced areas (so-called hot spots) at borough and LSOA level in explanation of their sociodemographic features; and (3) the most affected land use types over pan-London measured by mobility for future crime reduction and prevention, it aims to develop new forms of knowledge in order to target future projections around crime reduction, to help fill the gap between cutting-edge data analytics and strategic and operational policy-making, and make London a safer city post COVID-19 by making best use of data and digital technology. Crucially, given the importance of the 'policing by consent' ethos practiced by London policing, it also targeted to understand fluctuations in key societal factors both temporally and spatially, so as to improve services to Londoners through the use of evidence.

KEYWORDS: COVID-19, lockdown, mobility, crime, land use

1. Introduction

London, as the United Kingdom's (UK) capital, is a city of 8.9 million people spread across 32 geographic boundaries, so representing 1 in 7 people living in the UK and with political and social significance. COVID-19 has had a significant impact on the capital across a wealth of areas, e.g., economic slowdown and the rise in unemployment (Bosetti, Belcher and Quarshie, 2020). Here, we focus on exploring the impact on crime rates following COVID-19 in London. Since the outbreak of COVID-19, we have seen cliff drop in mobility hence witnessed large reductions across many crime types from last year (i.e., acquisitive crime, knife crime, as depicted in ***Results*** **Figure 4**), whereas others have seen increases (drug dealing, domestic abuse and anti-social behaviour). However, less is known around which geographic areas have been most impacted and why (drawing upon wider population and societal data) as well as making predictions as to what we will see in the future for recovery.

London had been in the first lockdown for 7 weeks since 23rd March[†]2020 into early May, when Prime Minister Boris Johnson announced it officially in a national television address, with rules being laid out including closure of schools, restricted reasons for leaving home and social mixing prohibited, shops, restaurants, bars and all other hospitality venues were also forced to close while 'working from home' became standard for the very first time. The second lockdown commenced on

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[†]https://www.gov.uk/government/speeches/pm-address-to-the-nation-on-coronavirus-23-march-2020

31st October for an extended 4 weeks[‡], and the 3rd lockdown since December 2020 is still ongoing. Over the periods of lockdown, it was estimated to witness significant drop of mobility as indicated by figures published by the Cabinet Office that, UK road traffic levels have fallen by 73% since the 1st lockdown measures were introduced, and are at their lowest since 1955 (Damian Carrington Environment, 2020). However, in the between of first 2 lockdowns, there was a 4-week Eat Out to Help Out Scheme from 3rd August to 31st August[§], when large increase of London restaurant bookings was seen through OpenTable[**] platform, as opposed to its almost zero bookings during the 2 lockdown periods.

So, by taking the 1st and 2nd lockdowns as research Period 1 (23rd March to 10th May) and Period 3 respectively (31st October to 2nd December), the 4-week August time had been chosen as Period 2 (3rd August to 31st August) to compare the crime-deterrent or criminogenic effects from mobility change among boroughs. In general, this study aims to explore the influences from aforementioned mobility change over 3 periods on London crime levels in: (1) how about the deeper geographical split by crime type among boroughs and LSOAs; (2) what are the most influential land use types relating to significant crime change; (3) is there any regional featured crime change over the named 3 periods could enable local boroughs work on their future priorities strategies towards crime reduction; (4) are there any city wide targets could be suggested towards a more resilient Mayor's Police and Crime Plan upon such pandemic in the future.

2. Data and Methods

Since the first confirmed case in the UK recorded in January 2020, the Public Health England (PHE) kept releasing the COVID-19 confirmed cases and death cases data on daily basis; alongside related data published by NHS and Office of National Statistics (ONS), it could be applicable to visualise the general picture of total confirmed cases among London boroughs in **Figure 1** over the research periods (as of 7th January 2021), with blue-yellow-red colors indicating for the gradual increases of cases levels.

Figure 1 Accumulated data reflected the high infected boroughs

It exhibited unbalanced distribution of confirmed cases among London boroughs, with higher infections acccumulated in the northeast and southeast, opposing to the lighter infections recorded in central London and the the southwest. It was assumed that, the levels for confirmed cases among London boroughs were highly related to respective demographic and socio-economic profiling, as well as the mobility change over research period, all of which could further be considered as the

‡ https://www.bbc.co.uk/news/uk-54763956
§ https://www.gov.uk/guidance/get-a-discount-with-the-eat-out-to-help-out-scheme
** https://www.opentable.com/state-of-industry

features influence crime change accordingly. In order to identify the features might be indicative for crime change over research Period 1, 2 and 3, the following data had been collected and processed:

- Crime data: crime cases data for Period 1, 2 and 3 from Met Police crime data dashboard, then aggregated at both LSOA and Borough level for further analysis.
- Mobility data: collected from London Datastore through Google Mobility Reports[††], upon aggregating locational data shared by users of Android smartphones onto London boroughs, to compare the time and duration of visits to the 6 categorized places (retail and recreation, groceries and pharmacies, parks, residential, workplaces and transit stations) to the baseline day before social distancing measures were introduced.
- Demographic, socio-economic data: contextual data collocated from Census 2011, and Deprivation Index data released in 2019.

Upon exploratory data analysis on crime change, mobility change by land use type and COVID-19 influences breaking down at borough level in the 3 targeted periods, it would be possible to identify the "hot spot" boroughs and "hot" land use types relating to significant types of crime change, for further analytical investigation; on the other hand, the demographic socio-economic contextual variables will be clustered by machine learning DBSCAN algorithm among London LSOAs as the contexts, hence working out the weights for each LSOA in later land use composite (LUC) index calculation; the selected 3H ("hot spot" borough, "hot" crime change type and "hot" mobility land use) targets will be analysed into LSOA level, in relation to its demographic socio-economic cluster context. In recognition of the features important to crime change in the 3 periods, random forest tree (RF) will be used to project future crime change at LSOA and Borough level, and geographically weighted regression (GWR) will be applied for prediction purpose; but most of important, working as the evidence suggesting London boroughs' crime prevention priority strategies in the near future.

The framework in Figure 2 includes the research design and core methods (i.e., Geographical weighted regression, random forest tree, machine learning for clustering) but detailed descriptions will be introduced in the final full paper.

[††] Source Data: https://www.google.com/covid19/mobility

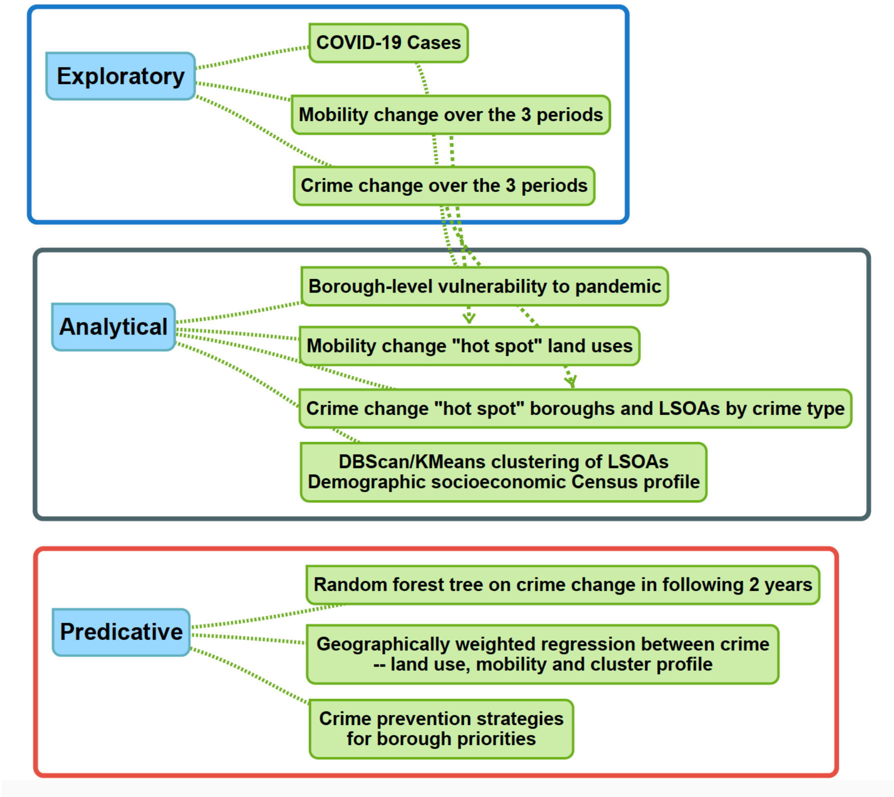


Figure 2 Workflow Diagram

3. Results (part)

3.1 Exploratory Trends Over the 3 Periods

Following the outbreak, we have seen large reductions in the general volume of crimes across many crime types, as shown in Figure 3, during 2 lockdown periods, but a "recovery" back in the summer months.

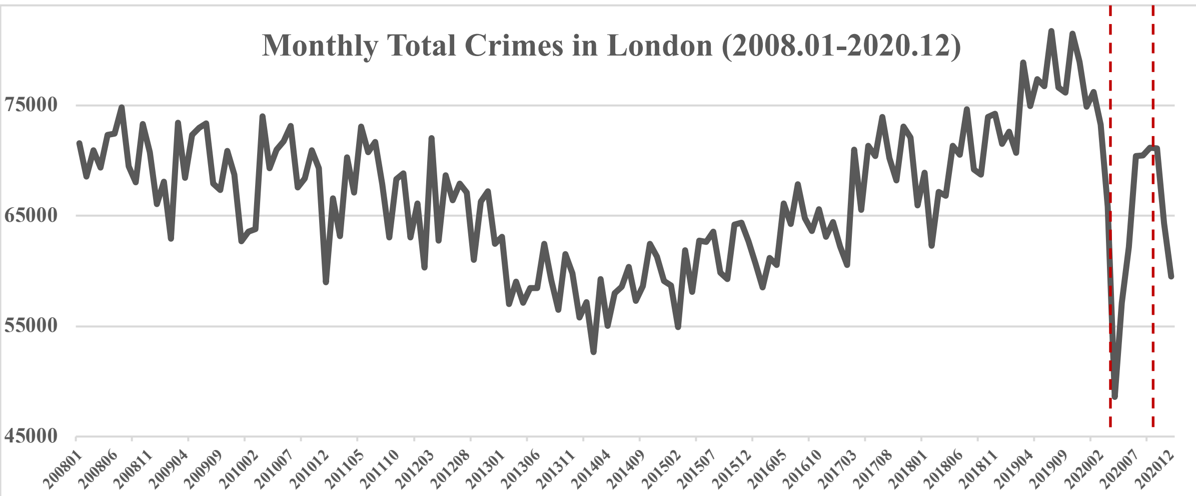


Figure 3 Crime Change in London (2008.01-2020.12)

In Figure 4 below, the most significant crime rate drop seen during the first lockdown Period 1 (March, April and May), occurred in the Theft and Robbery category, with on average over 50% decrease year-on-year, most dramatically in April. There were comparable decreases in Violence Against the Person, which dropped about 30% in April, and Possession of Weapons, which dropped over 30% in March. However, some other crimes such as Domestic Abuse and Anti-Social Behaviour saw large increases over the period comparing to 2019. For example, Drug Offences increased over 50% in May comparing to 2019 [2].

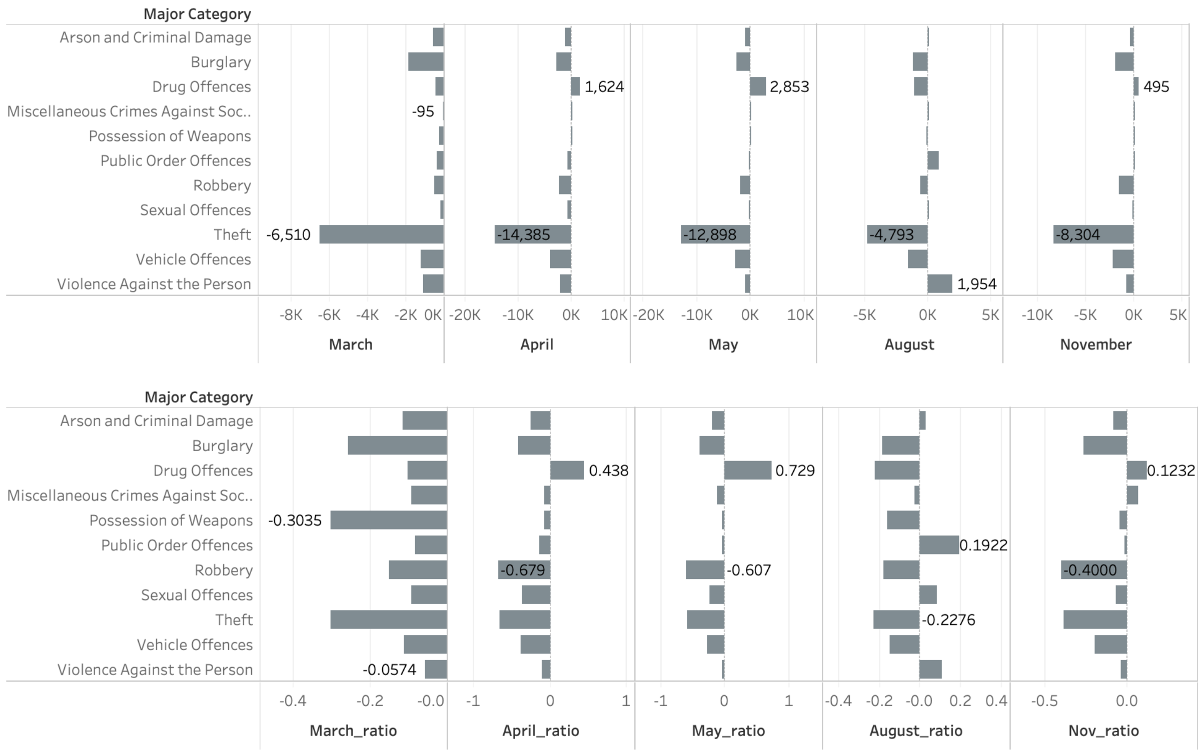
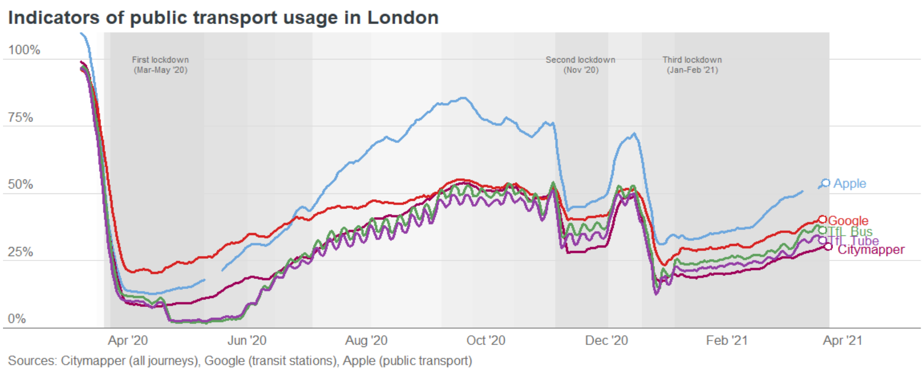


Figure 4 Crime Change by type (March, April, May, August and November 2019 vs. 2020)

Since the August "Eat-out-to-help" scheme rolled out, expressive crimes saw significant increase in Period 2 comparatively, i.e., Public Order Offences, Violence Against the Person, Sexual Offences and slightly increase in Arson and Criminal Damage. In the meantime, acquisitive crimes like Theft, Robbery, Burglary and Vehicle Offences kept the decreasing trend as did in Period 1 and Period 3. Only Drug Offences exhibited the drop trend in Period 2, comparing to its increases during all the 2 lockdown periods.

Observed from Figure 5, the mobility changes in 3 target periods paralleled with the crime change trends, hence it was proposed that changes in mobility, especially the reduced use of public transport in London during the lockdown, could be considered as a driver of changes in crime. It was apparent



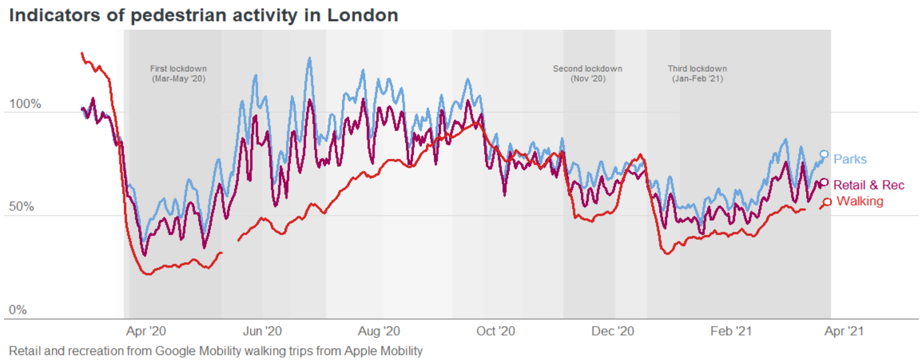


Figure 5 Mobility changes over COVID-19[‡‡] (London Datastore, 2021)

that citizens' mobility decreased at a relatively stable level in areas like High Street and Retail & Recreation areas, along with the walking trajectory over the observation periods, but the increase of mobility in Parks was of interest for exploring the most impacted areas. It was assumed that for Period 1, the pre-lockdown behaviour change effects on crime would be reflected in March, while the lockdown impacts on crime would be more reflected in May.

Among all the 6 land use types been analysed, there were not significant disparities among 3 periods for grocery and pharmacy (e.g., supermarkets), transit stations, workplaces and residences land use types, so they were only calculated directly for LUC index. On the contrary, land use type Parks, as well as Retail and Recreations exhibited significant variances between Period 2 and the lockdown Period 1 and 3.

Period 1 **Period 2** **Period 3**

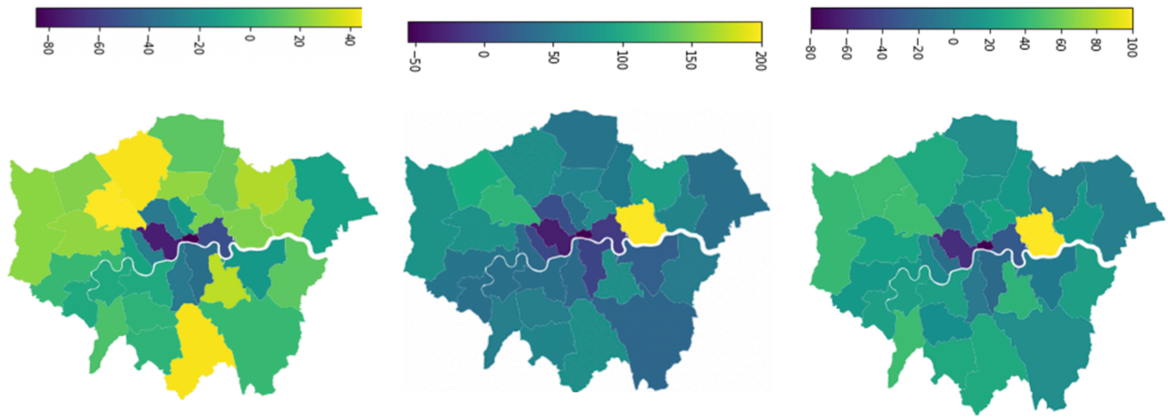
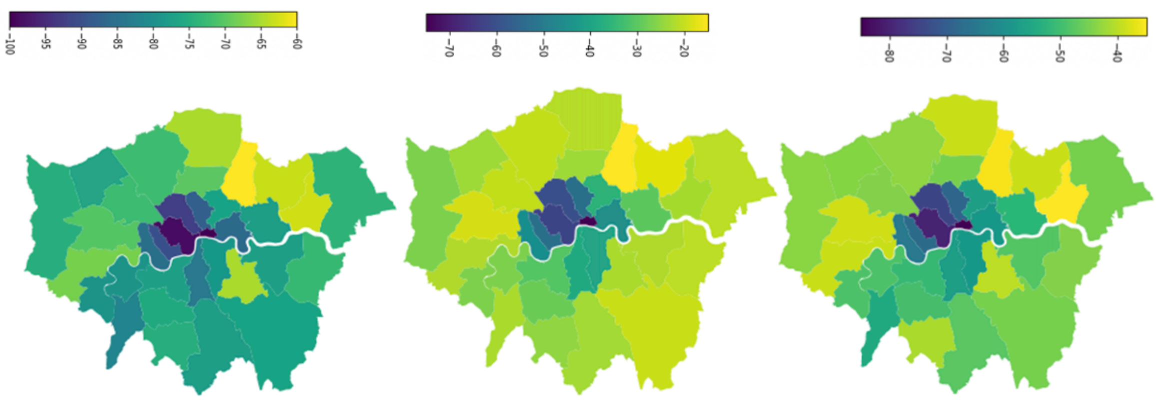


Figure 6(a) Mobility Change in Parks Land Use



‡‡ https://data.london.gov.uk/dataset/coronavirus-covid-19-mobility-report

Figure 6(b) Mobility Change in Retail & Recreation Land Use

The land-use composite index (LUC) is designed to measure the influences on mobility change over the lockdown periods for each land use category, based on the relationship between land use and mobility change volume. Then, upon calculating the proportion of each category of land use in each borough, a final mobility-influential weight could work out for each target borough, which will be considered in later prediction models.

3.2 Analytical Exploration on Hot Spot Areas and Crime Types

Analytical explorations on the main crime change contributors by type, the land-use composite index (LUC) and contextual Clusters at borough and LSOA levels respectively over the target periods. The crime change hot-spot LSOAs could then be identified for targeted periods, complimented by the cluster profiling of LSOAs and boroughs. In the following figures, LSOAs observed crime decreases will be colored in grey-black when darker color signifies for greater drop, while orange-red will represent for increases in crime from medium to major level.

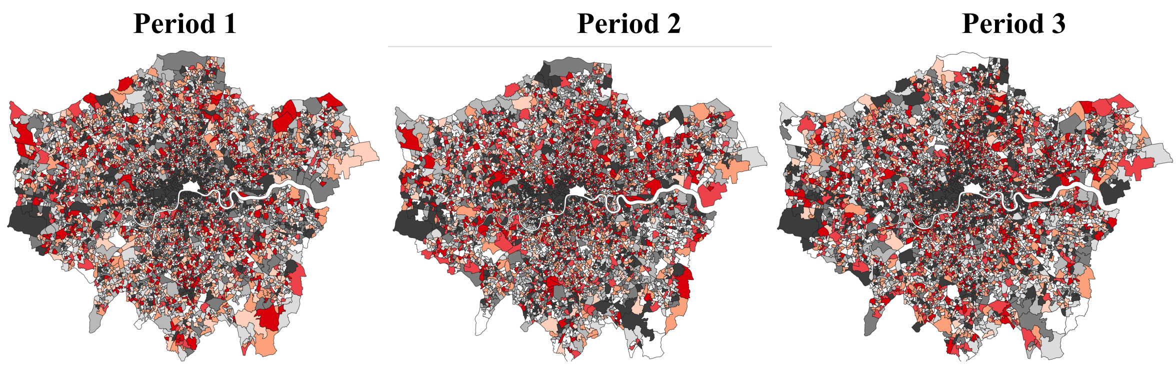


Figure 7 Crime Change hot spots among LSOAs in London

In Figure 7, the overall crime levels among all 4835 LSOAs in London had presented significant spatial distribution patterns in 3 target periods, in that crime increases tend to occur around outskirts London during the lockdown Period 1 and 3, but rebounced back in Period 2 towards the centre by spilling over to nearby LSOAs. It had experienced consistent crime plummets in Central London (i.e., Westminster City Council and the neighboring LSOAs) and Heathrow Airport area; whilst crime increases tend to be observed in the outskirt parcels, for example, the northwest end or the south end LSOAs. It is also worthwhile to investigate into areas like Havering, where exhibited significant crime bounce back in Period 2 from its drops in Period 1 and 3. To interpret the distribution, it is better to further investigate the main contributing types of crime to these changes in details.

3.2.1 Drug Offences crime change

On basis of the trend exploration of drug offences, it was suggested to look into the specific type of crime in April, May and November respectively.

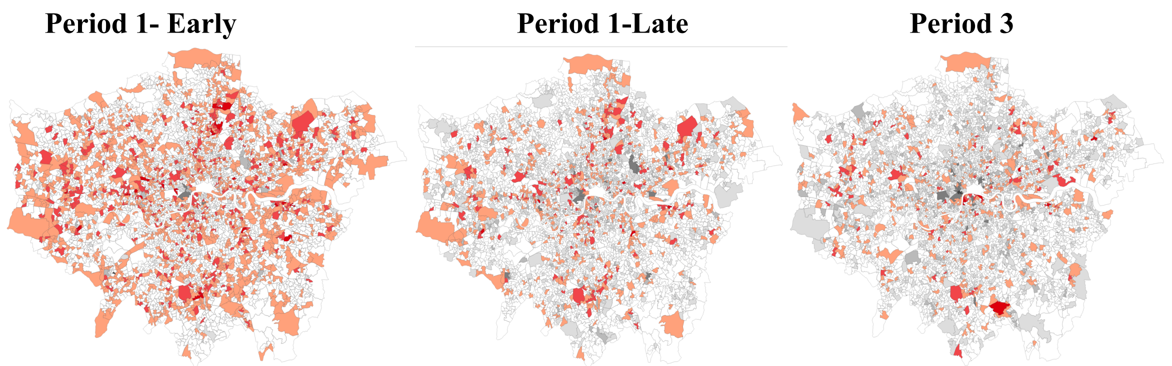


Figure 8 Drug Offences Changes among LSOAs during lockdown periods

During the 2 lockdown periods, it was recorded rocketing increases of drug offences spreading widely in early stage of Period 1 (April); but the LSOAs experienced significant increase of this crime had reduced in quantity largely over time, which could be observed from the Period 1 later stage (May) and Period 3 (November), but certain LSOAs in i.e., Enfield and Croydon, were found to deserve in-depth case studies.

3.2.2 Acquisitive Crimes

Referenced back to Figure 4, it had suggested by the results that Period 1 and Period 3 were experiencing large plummets of acquisitive crimes, like Theft and Robbery, among London LSOAs (Figure 9 and Figure 10).

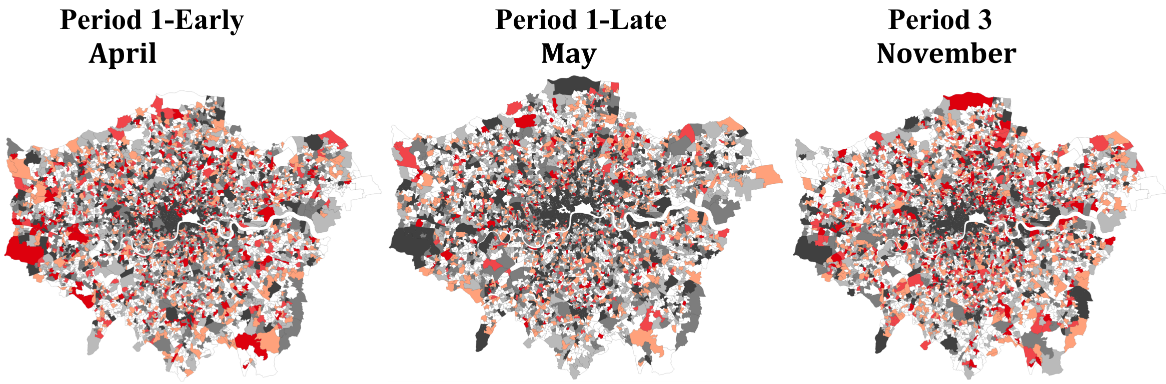


Figure 9 Theft crime changes in Period 1 and Period 3

Besides of the Central areas and Heathrow area, the bordering LSOAs in Bromley and Havering also saw dramatic drop of theft crimes; however, the general distribution indicated a gradually bounce back of thefts from Period 1 to Period 3 and tend to flat out across LSOAs parcels.

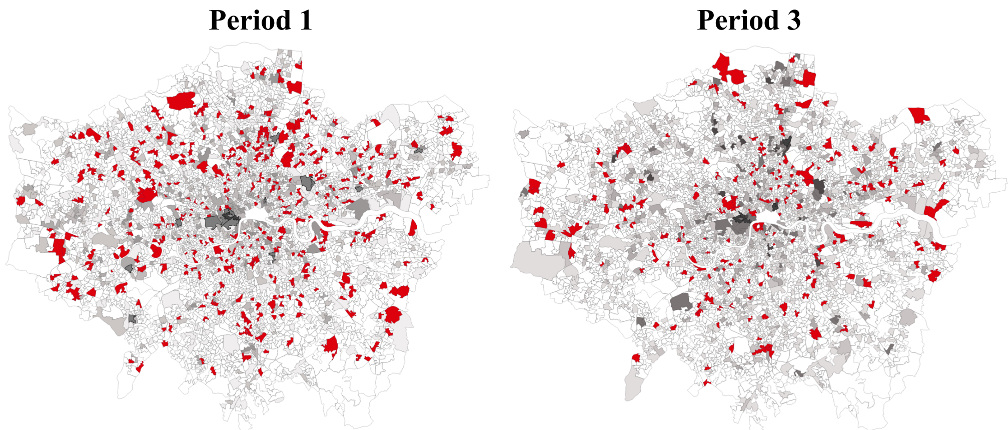


Figure 10 Robbery crime changes in Period 1 and Period 3

On the contrary, robbery crimes were still on decrease with Central London on stable dropping from Period 1 to Period 3, especially moved towards the outer LSOAs.

3.2.3 Expressive Crimes

The types for expressive crimes featured in each period altered, and only be prominent in March (Pre-Period 1) and August (Period 2). Hereafter, in the following figures (Figure 11 and Figure 12),

Figure 11 Expressive Crimes changes in Pre-Period 1

In March 2020, when the lockdown just kicked off, there were violence crimes against person increases in Heathrow area and several parcels which might be nearby to rail lines and caught the attention for further investigation.

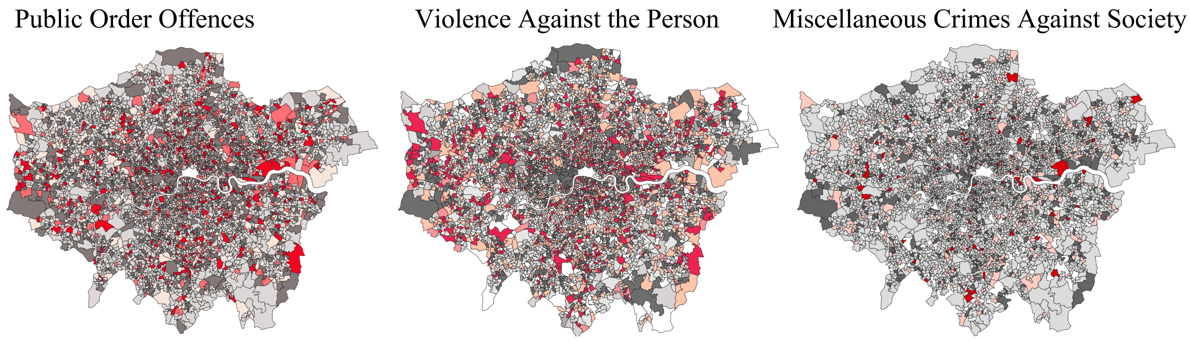


Figure 12 Expressive Crimes changes in Period 2

In Period 2 in August 2020, there were obvious increases of expressive crimes like Public Order Offences and Violence Against the Person in several LSOAs (i.e., in Bromley, Hillington, Newham), which were supposed to be explored against the contextual data.

3.2.4 LSOA Profiling Clusters

The local contextual profile are trained through clustering analysis, on basis of 2011 Census data collected from InFuse[§§] and NomisWeb[***] on the following 8 measures for each LSOA in London: Age structure, Ethnic group, wellings, household space and accommodation type, Tenure, Rooms, bedrooms and central heating, Car or van availability, Qualifications and students, Economic Activity by Sex. Machine learning algorithm DBSCAN on clustering had been called on through Scikit-learn package, to realise and visualise the 12 geodemographic profiling clusters for LSOAs, as the contextual parameters for later prediction model.

§§ http://infuse2011.ukdataservice.ac.uk

*** https://www.nomisweb.co.uk/home/detailedstats.asp?resume=no

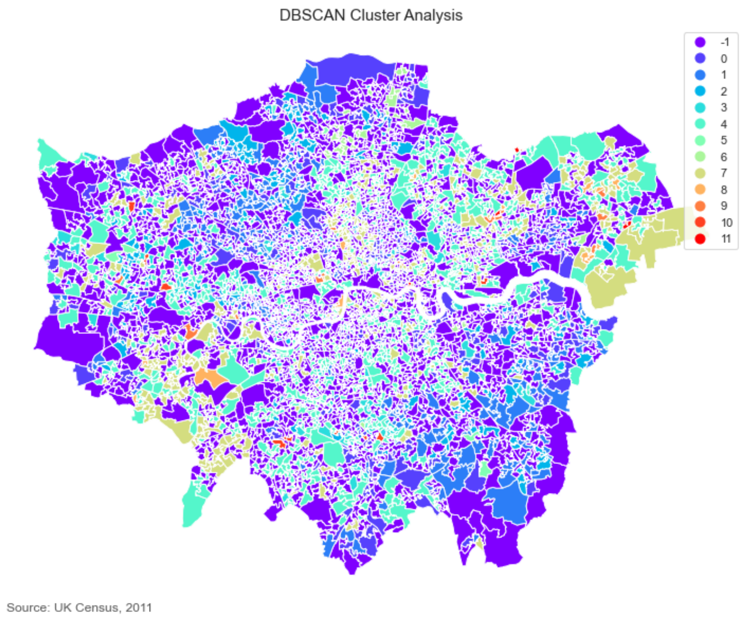


Figure 13 Demographic Socio-economic Profiling among LSOAs

3.3 Geographically Weighted Prediction

Since the 3rd lockdown had just announced to be lifted by end of March, it would be utilised to evaluate the predictive model's accuracy score in May 2021 when up-to-date data accessible.

3.3.1 Random Forest Tree on Mobility and Crime change predictions (ongoing)

3.3.2 Geographically Weighted Regression among LSOAs (to improve)

Training features included are the cluster index, and some regional disparity measures like the general Deprivation Index score (IMD), and Deprivation Indices scores for crime, education, income, employment, barrier to housing services, etc., but will still consider the land use composite index once worked out. Taking crime changes in Period 2 as an example, the results could be presented below in Figure 16. More work could be replicated for Period 1 and 3, as well as taking specific type of crime as the dependant variable in due course. The final comparison will be taken as indicative for crime change influential factors selection towards future crime prevention strategies.

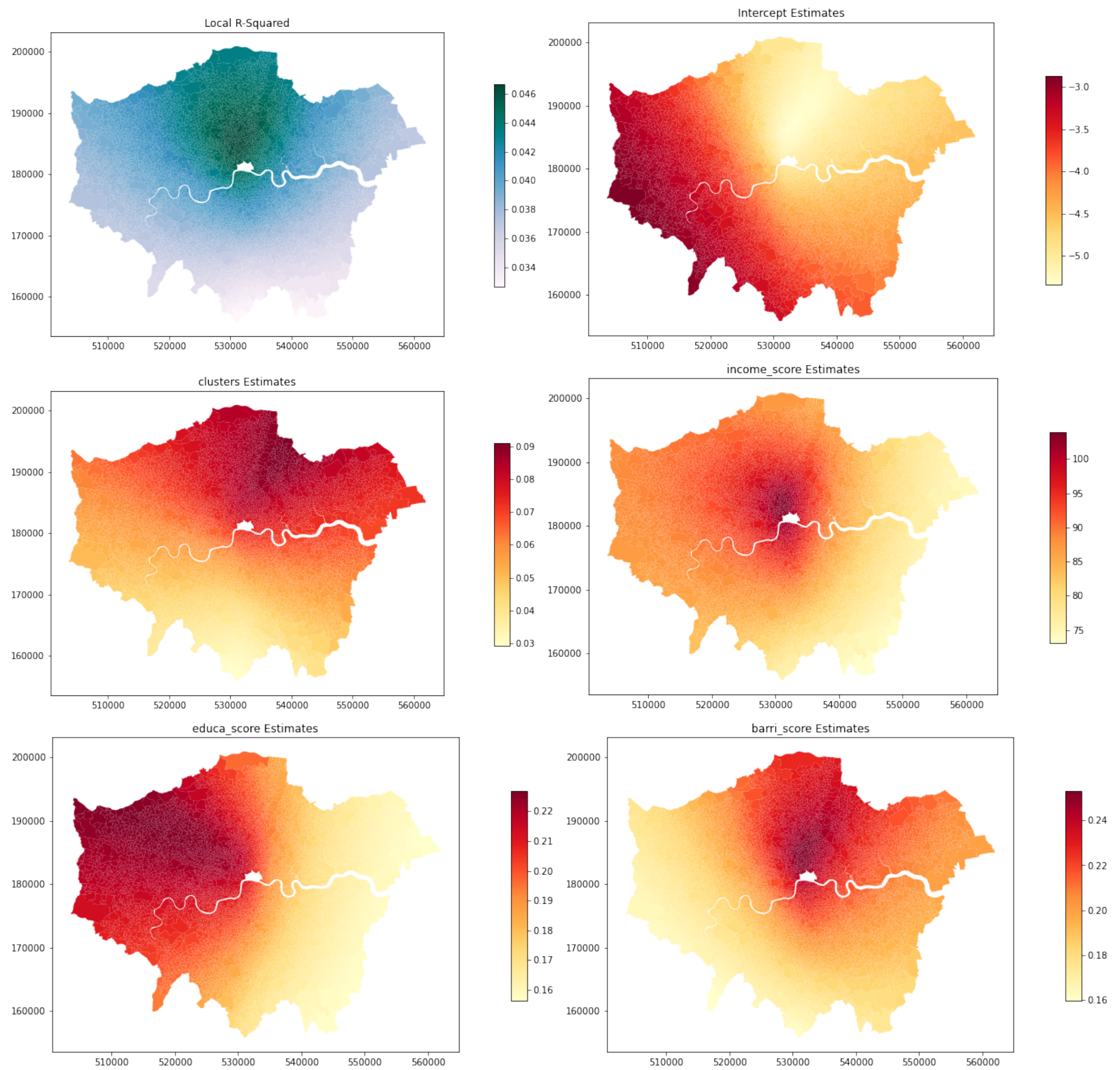


Figure 16 GWR model for Crime change in Period 2 (August) at LSOA level

Current model has stronger indicating "power" for crime change among LSOAs in Central and northern London, the baseline level of crime could be more predictable by this model in West London, with higher accuracy score; at the meantime, regional disparities measured by the deprivation indices also have spatial variations in that, income gaps play a crucial role of crime change in central London, while education gap scores more in the Northwest, and housing services gap is more indicative right in the North; the LSOA contextual profiling then is stronger in the larger North area. In total, current model to predict crime change in Period 2 will be more accurate in the North and West. Similarly, models will be tested for Period 1 and Period 3 for vertical comparison, and for 3 categories of crimes for horizontal comparison.

3.3.3 Geographically Weighted Regression among Boroughs (to improve)

At borough level, besides of the similar model at LSOA level, the model will further incorporate land use composite index to reflect the regional mobility influences. It aims to decide which geographical scale could be optimal applying the designed model, and which type of crime(s) could be more predictable in space to facilitate the borough crime prevention priority strategies.

4. Discussions and Conclusions

The work is still ongoing due to the up-to-date data, and succinct conclusions will be arrived in the coming months upon the releasing. It aims to build up a structured weighting matrix for each land-use category towards specific type of crime, followed by the final geographically weighted regression and random forest tree predication. The expected contribution for this research will be crime prevention suggestions to Mayor's Police and Crime Plan aiming for a more resilient recovery of London's safety against the pandemic.

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Biographies

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