GIS-based Health Risk Assessment

Course Work 2

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Abstract

In epidemiological research, both dispersion modelling (DM) and land-use regression modelling (LUR) are commonly employed to evaluate long-term exposure to air pollution, however, the reliability in estimating air pollution concentrations and the preference is unclear in literature. This paper compares both models for nitrogen dioxide (NO_2) concentrations for London and estimates the mortality burden of long-term (chronic) exposure to NO_2 for the resident population. The attributable risk (AR) and consequently the standardized attributable risk (SAR) was calculated and mapped for the region, and spatial autocorrelation techniques – Global and Local Moran's I were employed to map out the clusters at both LSOA and District Level. The results showed a difference between the total estimated risk for both spatial resolutions from both models, while a clustering of high attributable risk regions in and around the centre of London.

Introduction

Air pollution is composed of a complicated combination of gaseous and particulate pollutants, with particulate matter, ground-level ozone (O3), nitrogen dioxide (NO2), and sulfur dioxide (SO2) being the most commonly researched among them due to their significant impact on health. These pollutants are commonly referred to as classical air pollutants. In 2016, ambient and household air pollution were responsible for a significant proportion of global health issues, with 24% of stroke cases, 25% of ischemic heart disease cases, 28% of lung cancer cases, and 43% of chronic obstructive pulmonary disease (COPD) cases attributed to their effects. (*Who european high-level conference on noncommunicable diseases*, 2019) Epidemiological research has found links between various health outcomes and prolonged exposure (usually spanning over a year or more) to outdoor air pollution.

NO2 is a respiratory toxin gas that is mainly produced from the oxidation of nitric oxide (NO) in outdoor air. In urban regions, motor vehicle exhaust is the primary source of NO, NO2, carbon particles, carbon monoxide, and other pollutants. An increasing number of cohort studies have utilized spatial variations in NO2 levels over a prolonged period, estimated by pollution models that employ techniques like monitoring data interpolation, land use regression, or dispersion models. These studies have investigated correlations between long-term NO2 exposure and the incidence of disease or mortality. The US Environmental Protection Agency's Integrated Science Assessment evaluated the evidence for nitrogen oxides by examining toxicological and epidemiological evidence across various health outcomes. The assessment concluded that "the evidence hints at the possibility of a causal relationship between mortality among adults and long-term exposure to NO2, but it is not sufficient to infer such a relationship with certainty." (Atkinson *et al.,* 2018)

The initial stage in conducting an AP-HRA involves evaluating the exposure of the relevant population to particular air pollutants. Monitoring data can be utilized to estimate the exposure to air pollution for populations residing near the monitoring site, both presently and historically. The subsequent stage in the AP-HRA process involves determining the potential health risks associated with air pollution exposure. This necessitates the use of concentration-response functions (CRFs) that indicate the health impact per unit concentration of a specific air pollutant. Generally, these CRFs are established through epidemiological studies. (WHO,

2016) Apart from Dispersion and Land Use Regression models, satellite remote sensing, Source Apportionment and Health Impact Assessment studies can be used to undertake Health Risk Assessment. Remote sensing techniques use satellite imagery to estimate air pollutant concentrations and provide information about large geographic areas and is particularly useful for assessing pollution in regions with limited ground-based monitoring stations. (Judd *et al.,* 2018) Source apportionment methods use statistical techniques to identify the sources of air pollution at a specific location and can help to identify the most significant contributors to pollution. (Huang *et al.,* 2020) Health impact assessment (HIA) combines data on air pollutant concentrations with information on population demographics and health outcomes to estimate the health risks associated with exposure to air pollution. (Krewski *et al.,* 2009)

The aim of this paper is to estimate the mortality burden of long-term (chronic) exposure to nitrogen dioxide (NO2) for the resident population of London. The attributable risk (AR) to NO2 using a concentration response function (CRF) will be calculated and the mortality estimates for LSOAs and Districts from the Dispersion and the Land Use Regression model will be mapped and compared.

Methods

For the calculation of Attributable Risk, the CRF (1.03) (Walton *et al.,* 2015) and the background rate of disease B_R (630 deaths per 100,000) (Office for Health Improvement & Disparities, 2023) were considered. For the geospatial and statistical analysis Standardized Attributable Risk (SAR) is considered. The ASCII file provided for the LUR model was projected in ArcGIS Pro 10.6 and the values to point was exported for the postcode locations in London. The raster values obtained for the dispersion and LUR models were multiplied with the population counts at the postcodes to get the Population-Weighted exposures. The data for LSOAs and Districts were extracted to Excel to calculate attributable risk and consequently the standardized attributable risk. Mapping and Spatial Autocorrelation (Global Moran's I and Local Moran's I – contiguity edges corners or Queen's Case) was conducted in ArcGIS Pro 10.6.

Results

The spearman's rho for the two models to compare the Population-Weighted Exposure for the LSOA level was found to be 0.90 and the t-test value is 146.03. For the District level, the spearman's rho was found to be 0.98 and the t-test value is 27.62. The Global Moran's I index for both models to compare the Standardised Attributable Risk (Attributable Risk initially) and at both resolutions fell between 0 and +1 indicating clustering of similar values. Exact values reported further below in the illustrations. The Local Moran's I plot provides the location of the clustering with high values of SAR concentrating in and around the city centre while lower values clustering around the edges of the Greater London area for the LSOA level. The District level plots for Local Moran's I show that the higher concentrations of SAR values lie north of Thames while still concentrating in and around central London.

Total Estimated Risk

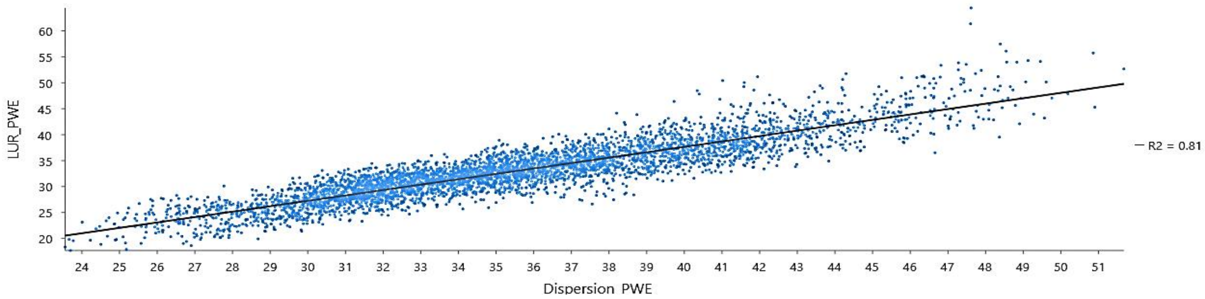
LSOA

Model – Risk Estimate	Sum	Average
Dispersion AR	5124.69	1.06
LUR AR	4781.93	0.99
Dispersion SAR	302510.80	62.67
LUR SAR	281963.12	58.31

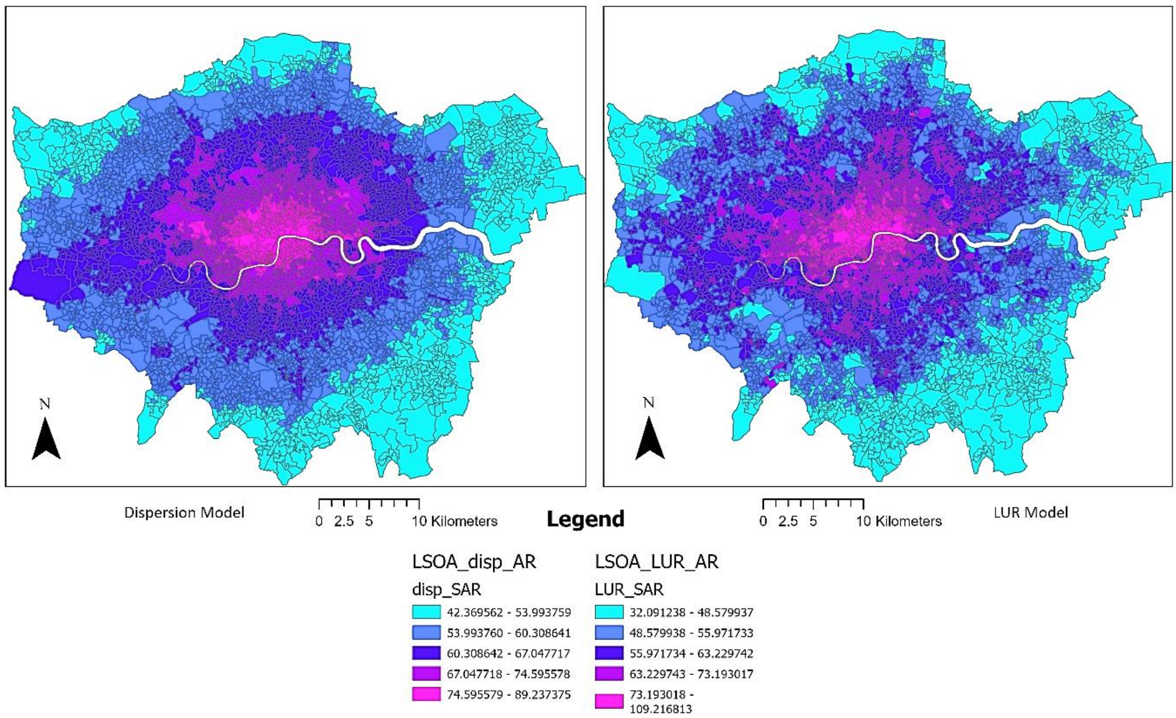
Districts

Model – Risk Estimate	Sum	Average
Dispersion AR	5125.74	155.32
LUR AR	4784.22	144.97
Dispersion SAR	2095.70	63.50
LUR SAR	1964.01	59.51

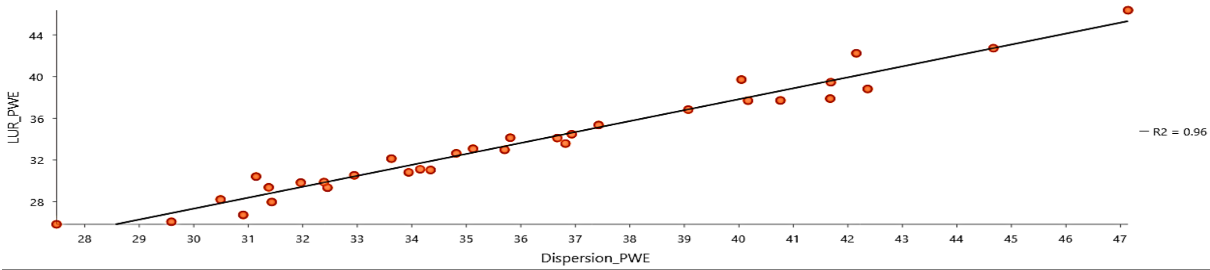
Relationship between Dispersion and LUR model PWEs for LSOAs



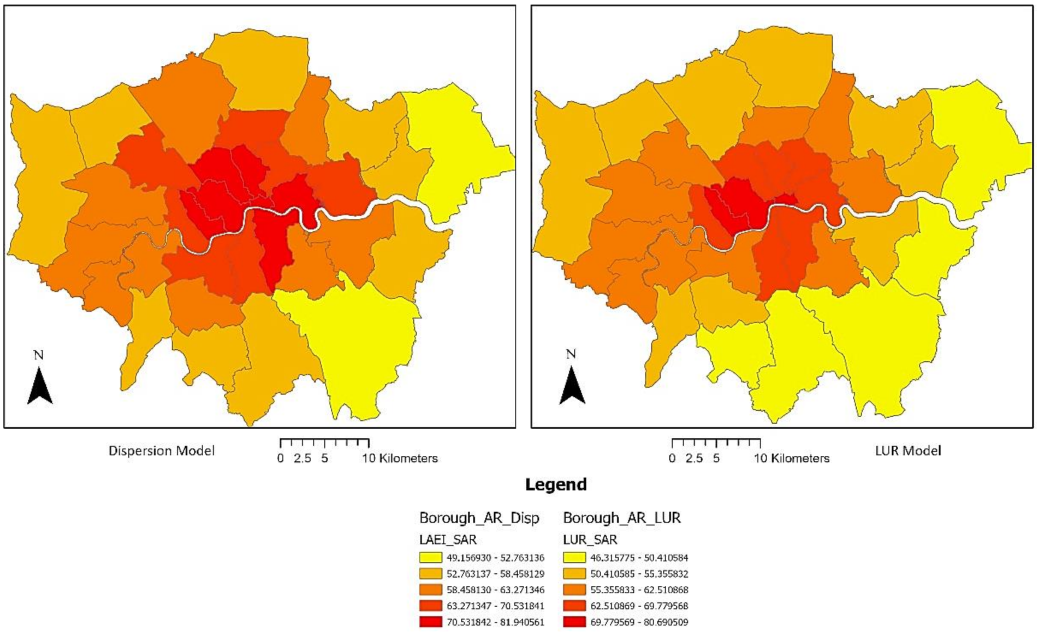
Standardized Attributable Risk London LSOA



Relationship between Dispersion and LUR models for Districts

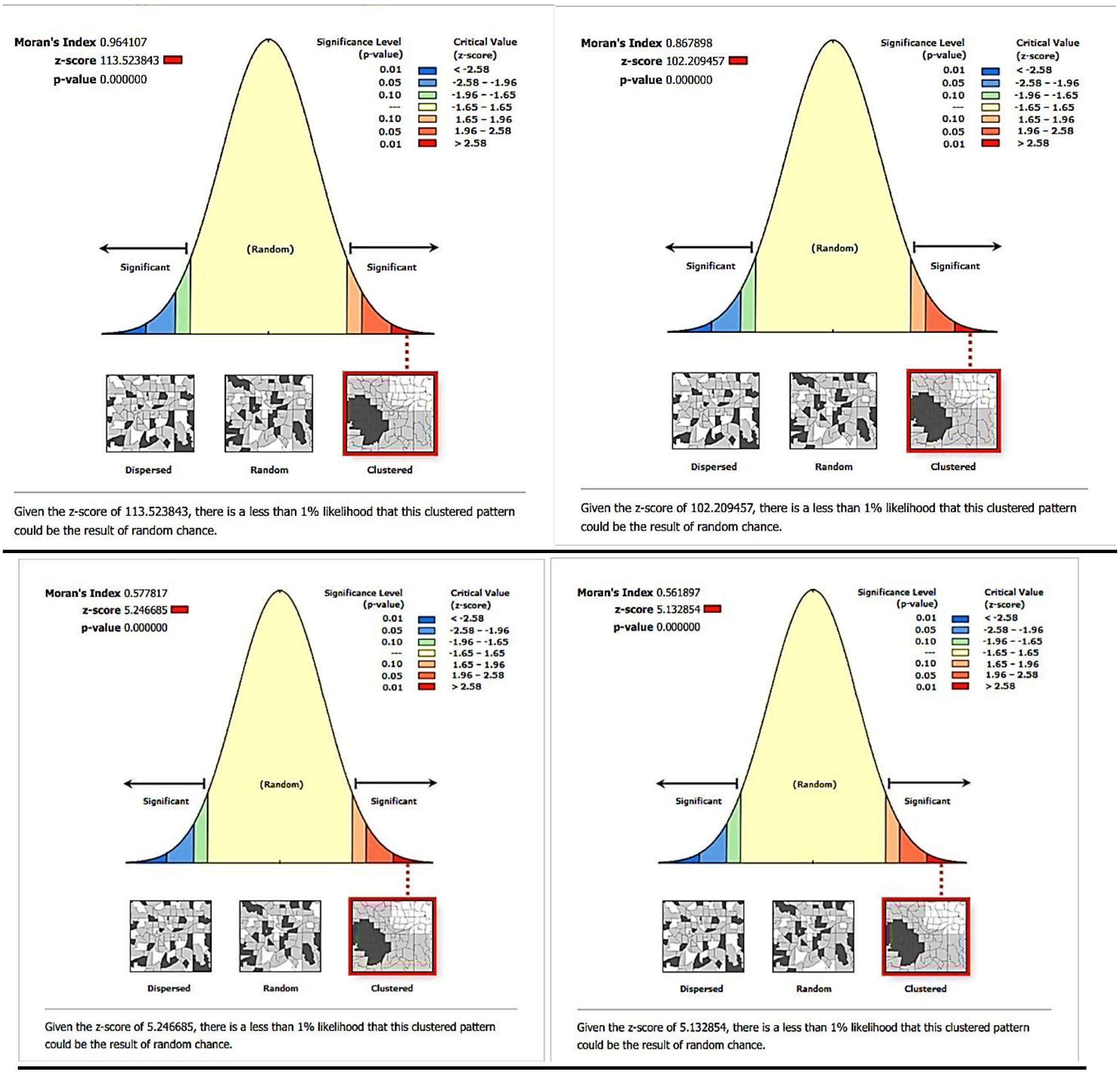


Standardized Attributable Risk London Districts



LSOA

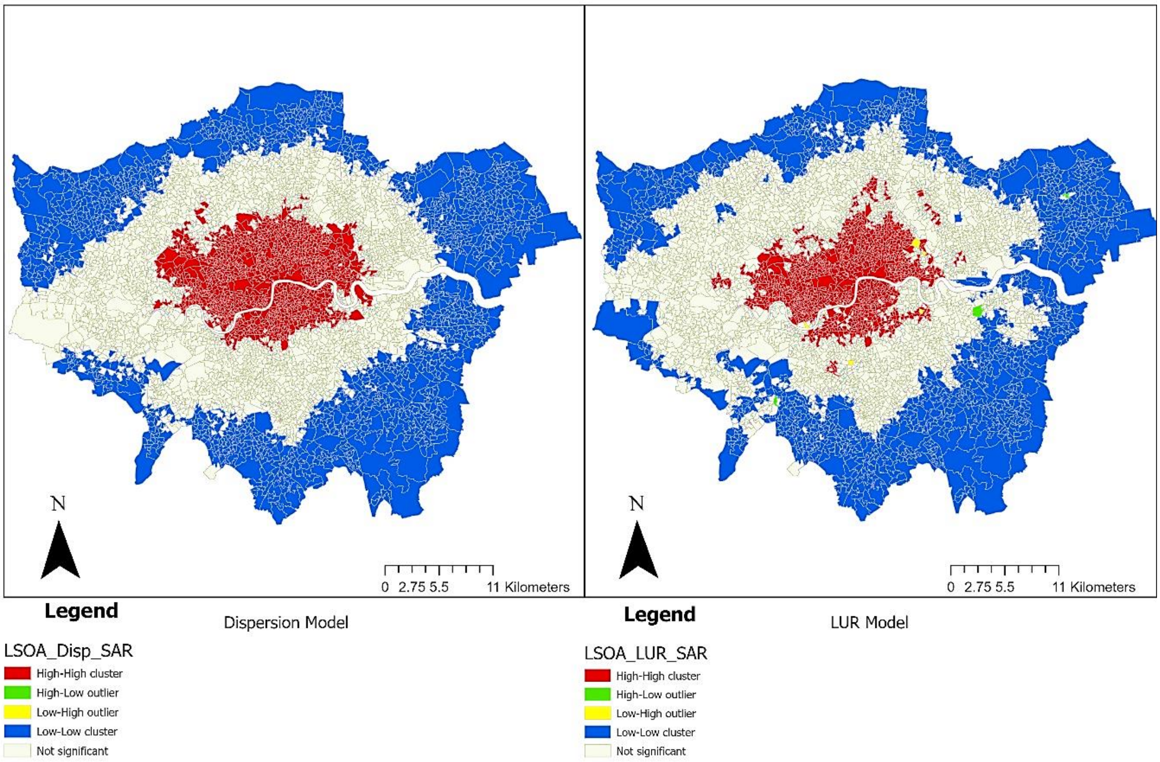
Borough

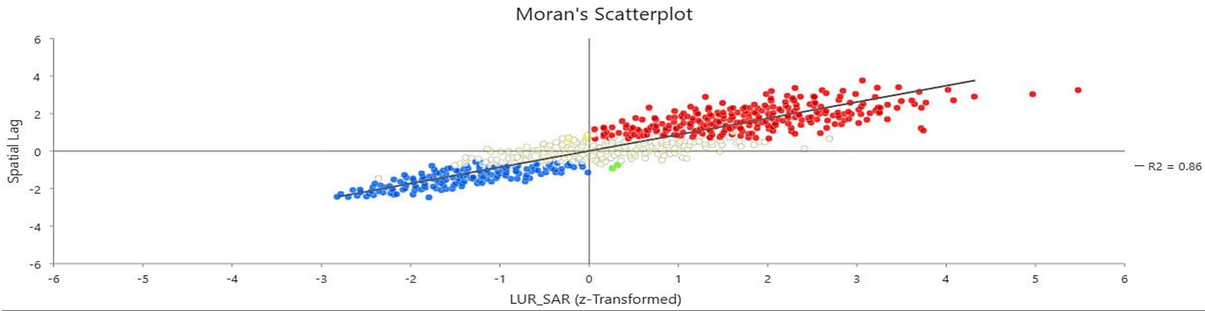


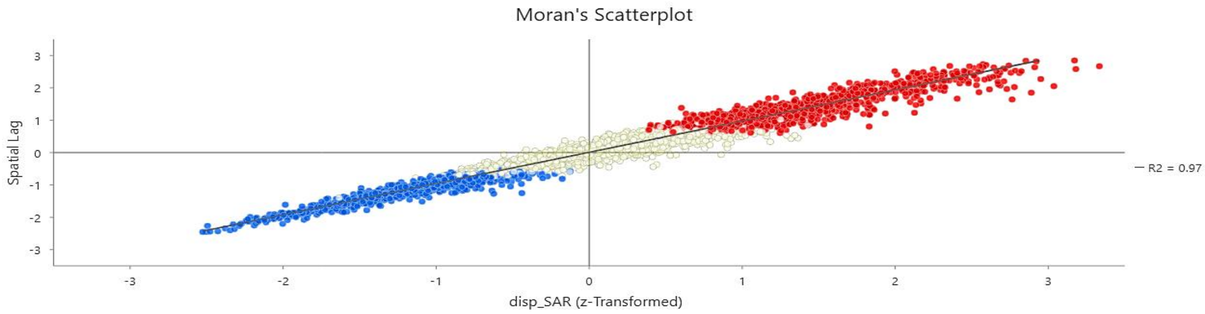
Dispersion Model **LUR Model**

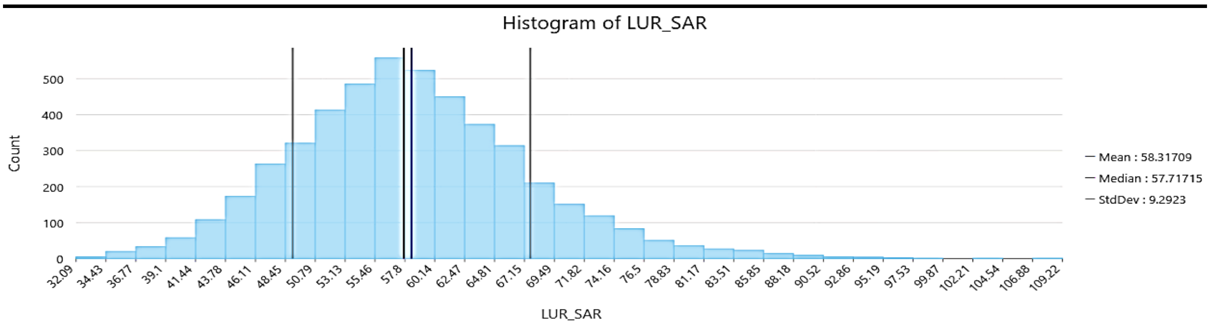
Global Moran's I

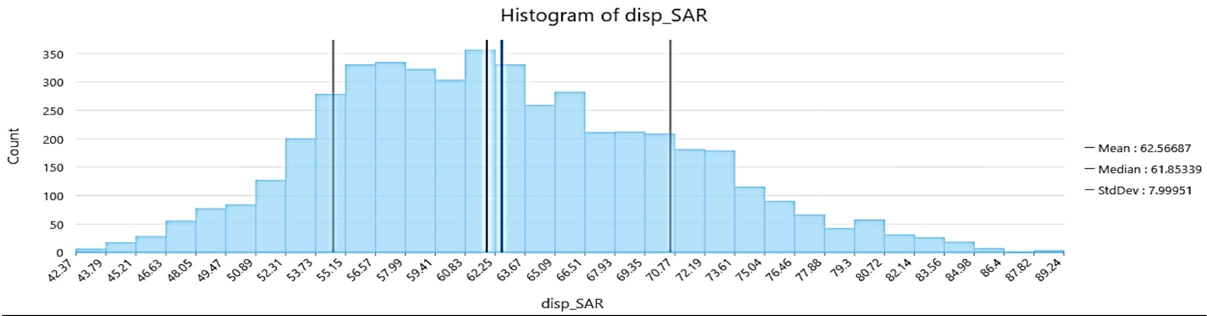
Local Moran's I - Dispersion and LUR Models for London LSOAs



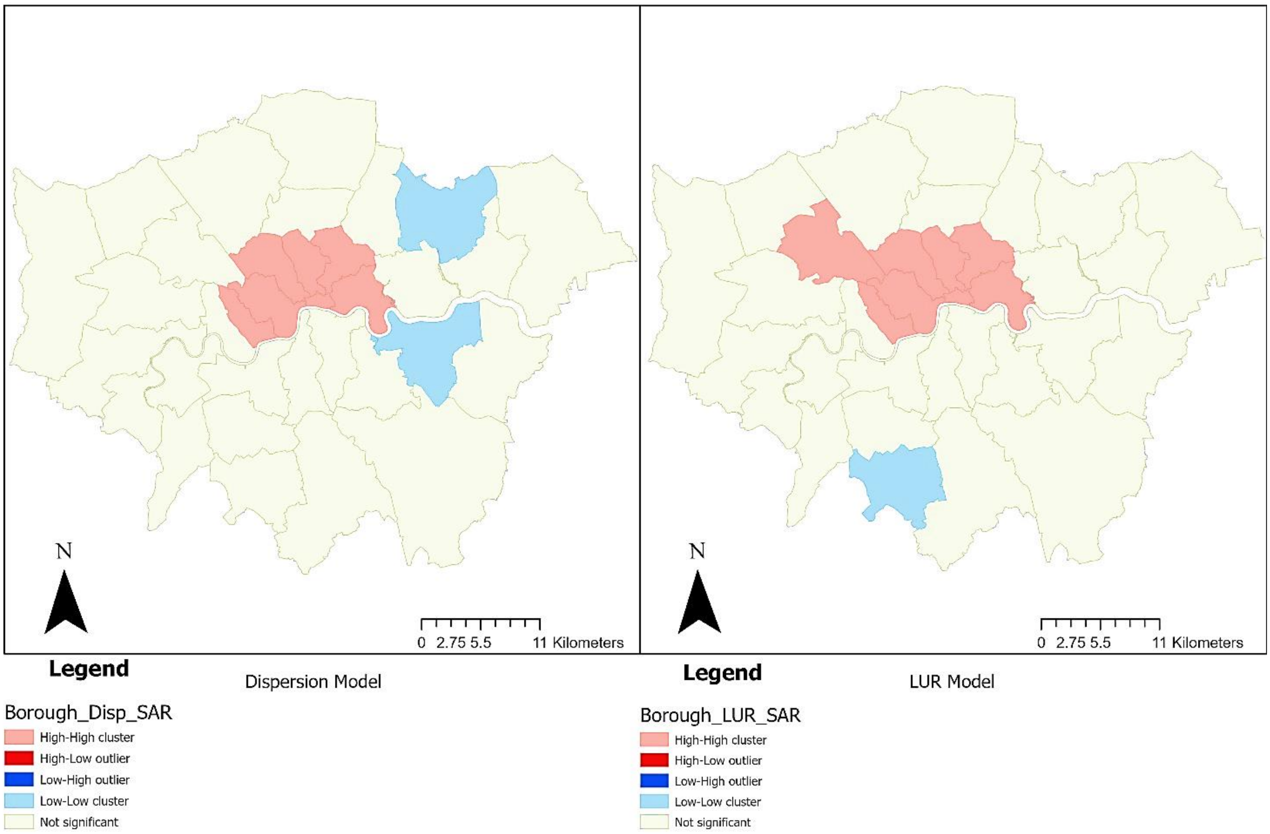


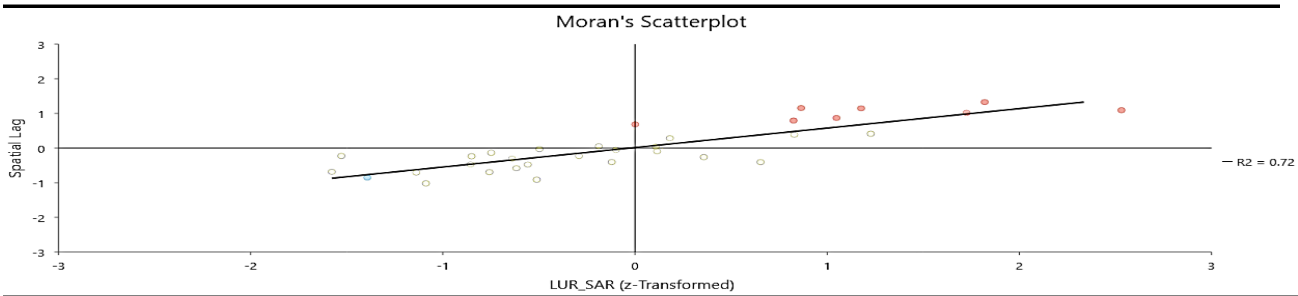


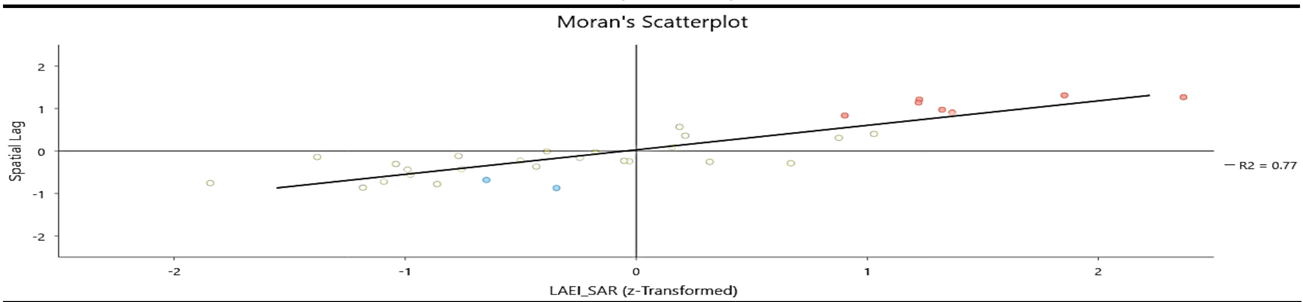


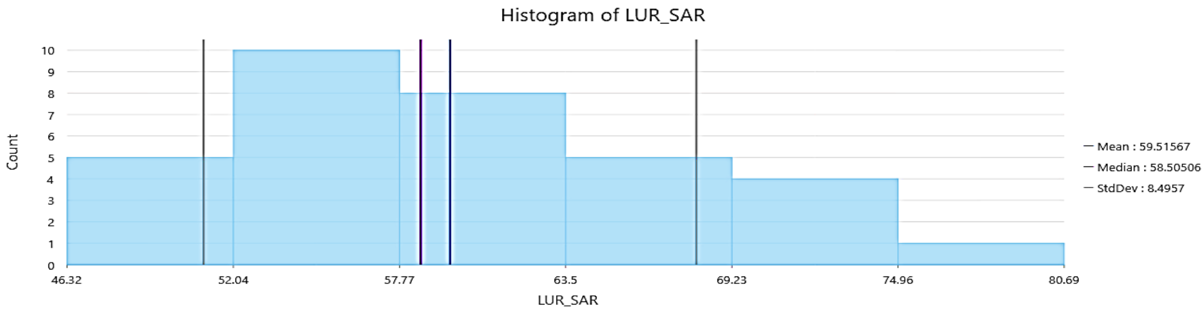


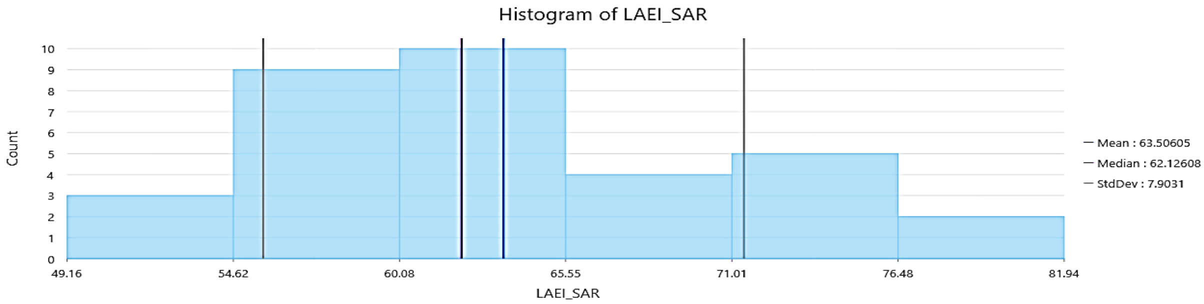
Local Moran's I - Dispersion and LUR Models for London Districts











Discussion

The stochastic or regression modelling technique utilizes statistics related to land-use, traffic counts, and other pertinent data to forecast the spatial distribution of pollutants in a particular area. In contrast, dispersion modelling involves using emission inventories alongside atmospheric dispersion calculations to describe how pollutants propagate geographically. Constructing emission databases for use with dispersion modelling can be a time-intensive process requiring specialized programming skills and costly software. Hence, utilizing regression modelling, which is based on readily available field measurements and existing data on traffic and other pertinent variables, may provide a cost-effective and straightforward substitute.(Rosenlund *et al.,* 2008) The total attributable risk and consequently the standardized attributable risk was greater for the dispersion model at both spatial resolutions, while the spearman's rho for the population-weighted exposures was closely correlated at 0.90 at the LSOA level and 0.98 at District level. Spatial Autocorrelation techniques revealed the presence of high AR clusters in and around the central region while low AR clusters at the edges of the study area, similar to studies that mapped other pollutants like $PM_{2.5}$, PM_{10} and other factors like noise pollution predominantly due to traffic. (Fecht *et al.,* 2016) While other studies have shown that LUR and DM surfaces produce better results for NO_2 concentrations, the correlation between the two reduces at a lower spatial resolution.(de Hoogh *et al.,* 2014) This was dissimilar to the finding in this paper, with the spearman's rho increasing as the analysis shifted from LSOA to District level. A hybrid LUR-DM model is suggested to improve the accuracy of NO_2 concentrations, and therefore further exposure and risk estimates. (Korek *et al.,* 2017)

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