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Carbon Emission and Annual Income in the Britain in 2019: An Intra-regional Spatial Analysis

Yixuan Han[1,a,*]

[1]*Department of Geography, University College London, Gower Street, London, United Kingdom*
a. yixuan.han.20@ucl.ac.uk
**corresponding author*

Abstract: This study conducts a comprehensive spatial analysis of carbon emissions and annual income in Great Britain in 2019 using data from the Office for National Statistics (ONS) and the Annual Survey of Hours and Earnings (ASHE). Using spatial autocorrelation techniques, especially Local Moran's I, I identify significant spatial clusters, where Low - Low carbon emission areas are located in Manchester, West Yorkshire, Dorset and Wiltshire. In contrast, High-High clusters occur in Moray, the Midlands, South Yorkshire and Lancashire, highlighting areas where carbon emissions are spatially correlated. In addition, this research uses geographically weighted regression (GWR) analysis to identify any existing relationship between annual income and carbon emissions with accounting of geography. The results show a consistent trend in the strength of this relationship, decreasing from northwest to southeast across the Great Britain. The highest coefficients are concentrated in eastern regions such as the South East, London and the East of England. This research aims to contribute to the understanding of spatial heterogeneity of the local environmental economics by informing relevant stakeholders and politicians about which regions are most in demand of targeted interventions. By identifying vulnerable areas, this study provides valuable insights into the UK's pursuit of sustainable development and low-carbon economy with the global movement towards green economy.

Keywords: Carbon emission, Sustainable development, Carbon footprint, Spatial analysis, United Kingdom

1. Introduction

1.1. Research Background and Significance

The spatial analysis of carbon emissions and annual incomes in Great Britain in 2019 is a pivotal study that can provide valuable insights into the intricate connection between economic prosperity and environmental stewardship. Understanding the spatial distribution and localized patterns of carbon emissions has become critical in the context of a changing environment with increasing awareness of green development and importance of varied locality [1]. At the same time, examining the relationship between carbon emissions and annual income has been largely discussed in the past literature, the correlation is relatively dynamic along with the hypothesis of environmental Kuznets curve (EKC) hypothesis [2]. However, the geography factor is also embedded under such relationship, therefore, understanding this at the spatial scale in higher resolution could provide an opportunity to assess the environmental impacts of economic growth and regional differences within regions and countries.

The year 2019 is of significance as it predates the global disruptions caused by the COVID-19 pandemic, allowing for a more stable assessment of the environmental and economic dynamics. The total CO^2 emission in the United Kingdom has shown a consistent decreasing trend from 2018 which is 476,894 kt while reaches 400,198 in 2020 when pandemic and lock-down begins [3]. Where the carbon emission change during pandemic is widely discussed, but such decline is considered as temporary rather than sustainable [4]. Therefore, this research aims to investigate the spatial pattern of the decline and its relationship with yearly pay shortly before the onset of the global pandemic in intra-regional geographical units with higher resolution.

This spatial analysis aims to reveal patterns, hotspots, and variations in carbon emissions and income across different local authority districts within the Great Britain with a higher resolution. It will identify regions with the most intense carbon emissions, those that are most affected by income level, and the foundation for local policy amendment to achieve the balance between economic development and environmental conservation. Ultimately, this study contributes to the broader understanding of the importance in higher-resolution spatial analysis in sustainable development.

1.2. Literature Review

The spatial analysis of carbon emissions and annual income in Great Britain has been widely studies and discussed by numerous literature that focus on interdisciplinary research in environmental economics. According to Jan Minx et al. analyses the carbon footprint in both rural and urban areas in 434 municipalities across the UK, identified the higher emission level in urbanized areas and the territorial CO^2 is highly correlated with residents' lifestyle [5]. Moreover, the research conducted by Baiocchi et al. underscores the role of social and consumer behavior in influencing CO^2 emissions by regression approach and using input-out estimator modelled to grouped data for different areas to discuss geographical variation [6]. Additionally, Helfter et al. explored a 3-year measurement fluxes for greenhouse gas and relevant spatial variability in London, identify the "missing" quantity beyond national statistics and unique symmetry of CO^2 compared with other GHGs [7]. Furthermore, the potential intervention to decrease carbon emission is also discussed, as evidenced by Symons et al., which proposed the idea that implement carbon taxes based on local consumer demand to decreases carbon emission by four efficient frameworks [8]. These studies collectively underscore the importance of spatial analysis in elucidating the complex relationships between carbon emissions, income, and socio-environmental factors.

The foundation of this paper lies in the exploration of the complex interplay between carbon emissions and annual income within the geographic context of this study area.

1.3. Research Content and Framework

This research adopts a robust methodological framework encompassing various elements. Firstly, next section introduces Local Moran's I, a spatial autocorrelation statistic recognized for its function to reveals clusters of high or low values of carbon emissions across Local Authority Districts (LADs). Statistical significance is determined through p-values, allowing researchers to identify areas with statistically significant spatial autocorrelation. This method is complemented by the creation of a cluster map that visually illustrates the spatial distribution of emissions disparities, portraying High-High and Low-Low carbon emission clusters in a manner that facilitates intuitive comprehension. Subsequently, the section also introduces Geographically Weighted Regression (GWR), a regression method with the accounting for geographical factors that explores the spatially varying relationships between carbon emissions and annual income across (LADs). Through GWR, this research seeks to identify the localized patterns of the dynamics between these two variables, thus providing deeper insights into the drivers of carbon emissions within specific geographic contexts.

The results and discussion section explain the scene of spatial heterogeneity and clusters of carbon emissions at the LADs level, offering a comprehensive understanding of the regions exhibiting concentration and divergence in emission patterns. Furthermore, GWR analysis uncovers the spatially dependent relationship between carbon emissions and annual income, enhance the comprehension of the drivers of emissions within unique geographical units. The point towards the future research direction, emphasizing the need for interdisciplinary investigations that consider additional socio-environmental factors and temporal dynamics. Critical thinking is also indispensable in this attempt to guide this collective effort to achieve sustainable and equitable development while mitigating the pressing challenges posed by global warming.

2. Methodology

2.1. Spatial Autocorrelation: Cluster of Carbon Emission

Spatial autocorrelation is a fundamental concept in spatial statistics that explores the degree to which neighboring geographic regions exhibit similarities in their attribute values. Local Moran's I, a widely used spatial autocorrelation statistic, provides insight into this localized spatial clustering [9,10]. It evaluates whether individual locations are surrounded by similar or dissimilar values relative to the entire dataset. The associated p-value for Local Moran's I helps determine the statistical significance of these clustering patterns. A low p-value indicates that the observed spatial clustering is unlikely to have occurred by random chance, signaling the presence of spatial dependency. Visualizing these results is often done using a Local Indicators of Spatial Association (LISA) map, where areas with significant local spatial clusters are highlighted. To accounted as much impact as possible, the significance level in this research is set as 0.1. LISA maps are invaluable tools for understanding spatial patterns, assisting stakeholders and researchers in identifying regions with unique geographical characteristics or patterns. The contiguity weighting used in this research is queen weighting, which helps to define the relationship between neighbors clearer compared with rook criterion as it uses both common edge and vertex [10].

2.2. GWR: Relationship between Carbon Emission and Carbon Income

Geographically Weighted Regression (GWR) is a spatial analysis technique that extends traditional regression models to account for geographical variation and spatial heterogeneity in relationships between variables [11]. In the context of studying the relationship between annual gross income (as an independent variable) and carbon dioxide emissions (as a dependent variable), GWR allows for the exploration of how this relationship varies across geographic locations. The first step in GWR is to define a set of spatial weights, in this case the Gaussian, which determine the influence of neighboring respondents on each data point with bandwidth that minimising the root mean square prediction error for the GWR [12]. These weights are used to estimate local regression coefficients for each geographical unit, allowing for spatially varying parameter estimates. GWR considers that the relationship between income and carbon emissions may differ from place to place due to unique local factors, such as economic activities, transportation patterns, population density or policy interventions. This methodology provides a valuable tool for uncovering complicated spatial patterns behind the simple OLS regression results and can help stakeholders develop location-specific strategies to address environmental concerns and socio-economic disparities.

The equation for GWR can be expressed as follows:

$$Y_i=\beta_0 (u_i,v_i)+\beta_1 (u_i,vi)\, X_i+\varepsilon_i \tag{1}$$

Where Y_i is the dependent variable (carbon emissions) for the i location. X_i is the independent variable (income) for the i location. $\beta_0(u_i,v_i)$ is the spatially varying intercept term, which varies by location and is influenced by the coordinates (u_i,v_i) of the i location. $\beta_1(u_i,v_i)$ is the spatially varying coefficient term for the independent variable, which also varies by location based on the coordinates (u_i,v_i) of the i location. ε_i is the error term or residual for the i location, representing unexplained variation or noise. i location in this research indicates the local authority district in Great Britain.

In GWR, both the intercept $\beta_0(u_i,v_i)$ and the coefficient $\beta_1(u_i,v_i)$ are estimated separately for each LAs, allowing the relationship between the dependent and independent variables to vary spatially. This approach accounts for spatial heterogeneity and provides a more detailed understanding of how the relationship changes with the accounting of geography.

3. Results and Discussion

In 2019, the UK's carbon emissions form a significant decline against the backdrop of continued global efforts to combat climate change. The year marked a significant point in the UK's journey towards reducing its carbon footprint as in that year the UK has become first major economy legislate the goal to achieve “net zero” by 2050 [13]. As the sequence 5-year plan is substantially achieved from 2008 when the UK Climate Change Act went through Parliament and legislated, the 2018-2022 goal is set to decrease 37% carbon budget compared to 1990 [14]. The carbon emission in all sectors has decreased 36% in UK range with notably 56% decline in North East from 2005 to 2019 [15]. In order to continue to meet the targets and maintain the current reduction status quo, the UK government has enacted a series of measures to achieve sustainable energy savings and emission reductions. Reducing reliance on electricity and traditional fossil fuels, the Net Zero Strategy specifically proposes the development of low-carbon energy such as hydrogen and biofuels, which will create more employments and boost the economy at the same time as strategic investments. Additionally, the transportation sector saw advancements in zero emissions vehicle (ZEV) adoption, transport carbon emission saw a decrease of 1.8% in 2019 compared to 2018, further contributing to the reduction of carbon emissions [13,15]. The year 2019 marked the continuing progress for the UK's ongoing commitment to combating climate change and transitioning towards a more sustainable and environmentally responsible future.

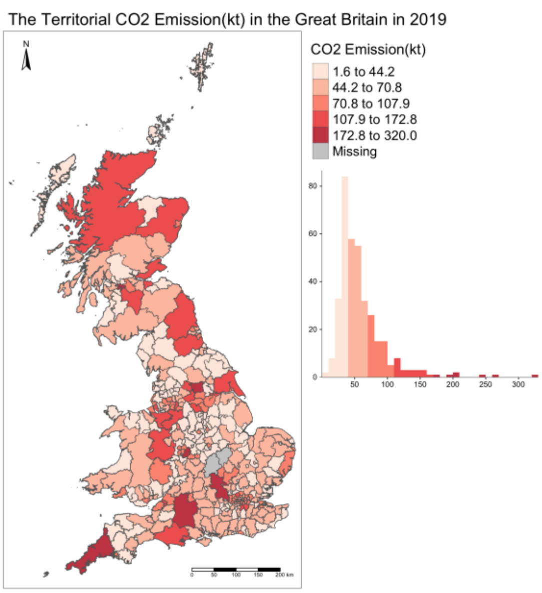

Figure 1: The Territorial CO^2 Emission(kt) in the Great Britain in 2019

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As figure 1 shows, the spatial distribution of carbon emissions in the United Kingdom reveals a complex pattern with distinct regional variations. Notably, carbon emissions tend to be higher in several key areas, including Scotland, North East, South West, and the West Midlands, as well as along the west coastal areas. These disparities in carbon emissions are influenced by various factors, including industrial activities, transportation networks, energy production, and population density. Regions like Greater London, Greater Manchester, Warwick, and the Scottish Central Belt are known for their relatively higher carbon emissions due to their urbanization and industrialization. Conversely, rural and less densely populated areas, such as parts of Wales and the Scottish Highlands, generally contribute less to the carbon emissions landscape.

3.1. The Spatial Heterogeneity of Carbon Dioxide Emission

The Local Moran's I statistics for carbon emissions in the UK reveals notable spatial patterns of clustering and dispersion based on the observation from Figure 2. For most LAs, the LMI value is between -1 and 1, values in this range suggest that the carbon emissions in these regions are not strongly clustered or dispersed but exhibit a relatively randomized spatial pattern. In other words, there is not a significant local spatial autocorrelation, indicating that emissions in these areas are not strongly influenced by the emissions of their neighboring regions. However, for some LAs in Yorkshire and South West, the value is even greater than 3. LISA values exceeding 3 indicate strong positive spatial autocorrelation, signifying the presence of statistically significant clusters of high carbon emissions in these regions. This suggests that these areas have localized hotspots of high emissions where neighboring areas also exhibit high emissions, possibly due to common factors like industrial zones or transportation hubs, such as Southampton and Sheffield. There are also LAs with LMI value lower than -1, which also locates at Yorkshire and South West. LISA values below -1 indicate significant clusters of low carbon emissions surrounded by neighboring regions with low emissions. This pattern suggests that these areas are distinct from their neighbors in terms of lower emissions, possibly due to factors like renewable energy adoption, emissions reduction policies, or geographical features. In summary, the interpretation of LISA values for carbon emissions in the UK reveals localised spatial patterns.

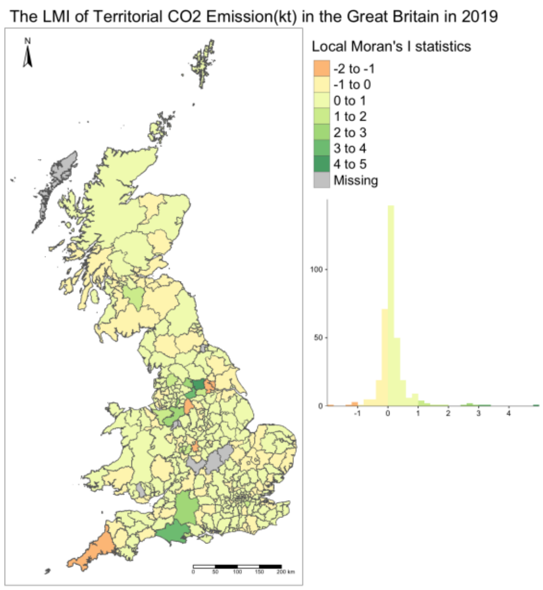

Figure 2: The LMI of Territorial CO^2 Emission(kt) in the Great Britain in 2019

Figure 3 shows the p-value of LMI values in all LAs, this result helps determine the statistical significance of observed spatial patterns. P-values above 0.1 suggest that for most regions, the observed spatial patterns of carbon emissions are not statistically significant. In other words, the patterns of emissions in these areas do not deviate significantly from what might be expected by chance alone. This indicates that there is not strong evidence of spatial clustering or dispersion in these regions. There are some LADs with p-value between 0.05 to 0.1. P-values falling in this range indicate a moderate level of statistical significance. For regions with p-values between 0.05 and 0.1, there is some evidence to suggest that the observed spatial patterns are not entirely due to random chance. These regions may exhibit subtle but potentially meaningful spatial clustering or dispersion in carbon emissions. P-values below the conventional significance threshold of 0.05 indicate strong statistical evidence of spatial autocorrelation. In the East Midlands and South West regions, the observed spatial patterns of carbon emissions are highly unlikely to be the result of random chance alone. This suggests that there are significant localised clusters or dispersion of carbon emissions in these areas, which may be influenced by specific factors like economic activities, industrial zones, or environmental policies.

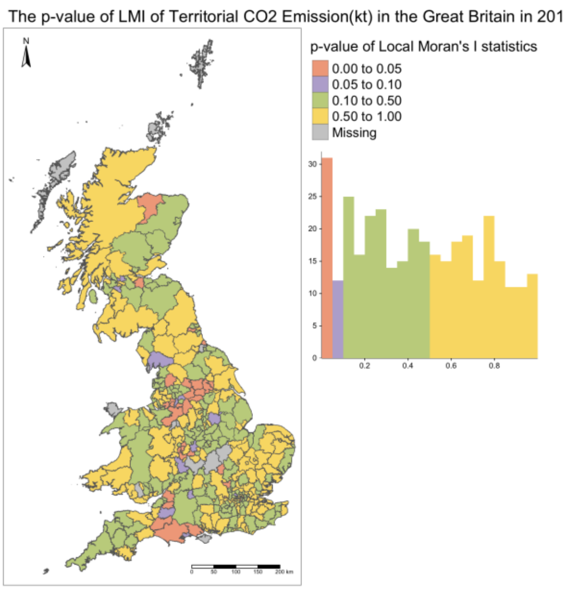

Figure 3: The p-value of LMI of Territorial CO^2 Emission(kt) in the Great Britain in 2019

As shown in Figure 4, the LISA value is compared with 0.1 significant level and the cluster map is created. The majority of regions on the map are not statistically significant in a 90% level, meaning that there is not strong evidence of spatial clustering or dispersion of the carbon emissions in these areas. Low-Low clusters indicate regions where low values of the variable are surrounded by other regions with low values. In this case, there are 17 regions exhibiting this pattern. For example, Manchester, West Yorkshire, Dorset, and Wiltshire are among these areas. This suggests that these regions have localized clusters of low carbon emissions, potentially due to common factors like environmental policies or economic characteristics. High-High clusters represent regions where high values of the variable are surrounded by other regions with high values. In this analysis, 26 regions are identified with this pattern, including Moray, central East Midlands, South Yorkshire, and Lancashire. This indicates the presence of statistically significant localized clusters of high carbon emissions in these areas, possibly influenced by shared factors such as industrial activities or energy production.

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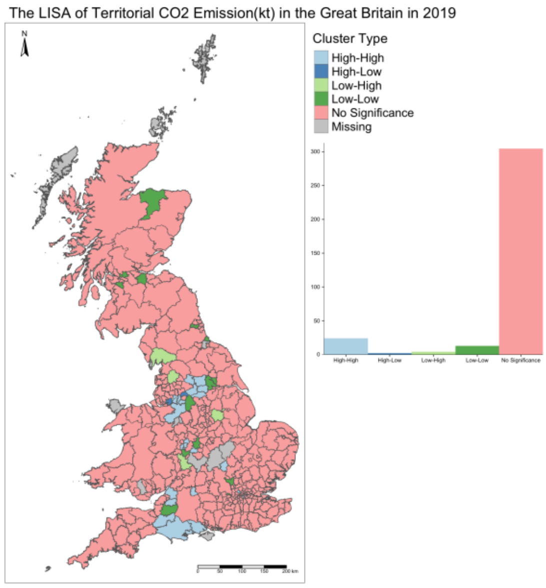

Figure 4: The LISA of Territorial CO^2 Emission(kt) in the Great Britain in 2019

3.2. Change of Correlation Between Carbon and Income

The GWR analysis conducted for examining the relationship between carbon emissions and annual income in Great Britain during the year 2019 has yielded noteworthy insights. Results are shown in Table 1. The mean coefficient of 0.0004121 signifies an overall positive association between income and carbon emissions on average.

Table 1: GWR results of Carbon emissions vs. Income, Great Britain, 2019

X. Intercept.	gwr_car. in_median
Min.:47.17	Min.:0.0003970
1st Qu.:47.34	1st Qu.:0.0004090
Median :47.52	Median :0.0004121
Mean :47.52	Mean :0.0004121
3rd Qu.:47.64	3rd Qu.:0.0004167
Max.:48.12	Max.:0.0004210

However, this relationship is far from uniform across the geographical landscape. The GWR analysis has unveiled spatial variability in these coefficients, with the maximum coefficient reaching 0.0004210 and the minimum at 0.0003970. This variability indicates that the strength of the relationship between income and carbon emissions varies significantly across different regions. Interestingly, there is a clear geographical pattern to this variation according to Figure 5, with coefficients generally decreasing from north to south and from west to east. The highest coefficients, signifying a stronger income-carbon emissions link, are concentrated in the eastern regions of South East, London, and East of England. It is important to note that the presence of missing values in the analysis can be attributed to data gaps in certain Local Authorities' annual income information. Additionally, the intercepts, ranging from a mean of 47.52 to a maximum of 48.12 and a minimum of 47.17, provide further context, suggesting baseline carbon emissions levels in these regions, which can be influenced by various localized factors and policies.

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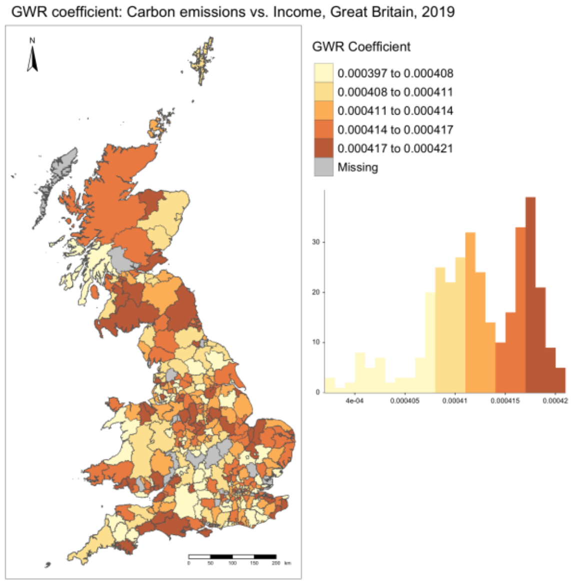

Figure 5: GWR coefficient: Carbon emissions vs. Income, Great Britain, 2019

4. Conclusion

In this spatial analysis of carbon emissions and annual income in Great Britain for the year 2019, drawing from comprehensive data sources from ONS and ASHE, this paper has unveiled crucial insights into the intricate relationship between economic prosperity and environmental sustainability. The methodology incorporated spatial autocorrelation, specifically Local Moran's I, to detect significant spatial clusters, and Geographically Weighted Regression (GWR) to assess the spatially varying relationships between these two critical factors. The identification of Low-Low carbon emission clusters in Manchester, West Yorkshire, Dorset, and Wiltshire, alongside High-High clusters in Moray, central East Midlands, South Yorkshire, and Lancashire, underscores the presence of localized disparities and opportunities within Great Britain. Furthermore, GWR analysis revealed a consistent spatial trend: coefficients generally decrease from north to south and west to east, with the highest coefficients concentrated in the eastern regions of South East, London, and East of England. This research serves a broader purpose, emphasizing the need for targeted policy interventions to align economic growth with environmental responsibility. Future research could enhance the granularity of the analysis by considering additional socio-economic and environmental variables. Additionally, addressing the limitations stemming from data gaps and model assumptions would refine the accuracy of research findings.

In critique, while this study provides valuable insights, it is important to recognize that the complex interplay between income and carbon emissions involves multifaceted factors beyond the scope of this analysis. Nevertheless, this research contributes significantly to the dialogue on sustainable development and informed decision-making in Great Britain.

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