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Spatial Analytics for Equitable EV Charging Access#

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ABSTRACT

Charging infrastructure is seen as the catalyst for electric vehicle (EV) uptake, which is essential to reach Net Zero targets. However, access to public charging and deployment of charging infrastructure in the areas most needed are key to increase EV ownership. This paper presents a framework based on K-means clustering and spatial analytics for the equitable deployment planning of EV charging infrastructure within South East Wales—a geographical region in the United Kingdom with low public charger deployment. Results show that there is a public EV charging divide between rural and urban communities in the region and, thus, a greater effort is needed to bridge the gap between these communities.

Keywords: EV charging infrastructure, equitable access, energy systems, K-means clustering, spatial analytics

NOMENCLATURE

Abbreviations	
WIMD	Welsh Index of Multiple Deprivation
G2SFCA	Gaussian 2-Step Floating Catchment Area
LSOA	Lower Super Output Area

1. INTRODUCTION

Decarbonisation of transport through the transition to electric vehicles (EVs) is critical to reaching Net Zero across the globe. Sales in EVs have consistently increased in the last years, with >14 million sold globally in 2023, which accounts for 18% of all new car sales in that year [1]. Ensuring adequate charging infrastructure is thus key to support the transition to renewable transport: If infrastructure lacks or is distributed inequitably, barriers to EV ownership will increase, especially for those unable to charge at home [2]. The large-scale rollout of EV charging infrastructure is not only a consideration for equitable access, but there are impacts on electricity grids, as increasing demands at scale will require further investment in distribution networks [3].

In Wales, United Kingdom (UK), Welsh Government released in 2021 a charging infrastructure strategy [4], which includes predicted public charging infrastructure to support the ban on petrol and diesel cars by 2030 [5]. To support EV rollout, the required number of chargers for a 'rapid charger deployment' would have had to increase by 2025 from 21 public chargers per 100,000 population to 640 chargers (and even further by 2030). For a 'fast charger deployment', 979 public chargers would had been required by 2025. However, as of January 2026, 120 chargers per 100,000 population have been deployed only [6]. At the same time, the ban on petrol and diesel cars has been subject to political turmoil, with the date for the ban to be in effect delayed to 2035 in September 2023 [7]. This was later changed in 2024 and 2025 to phasing out sales of new petrol and diesel cars by 2030 and hybrid vehicles by 2035 [8].

A market-led approach to the rollout of EV charging infrastructure often favours areas which are either commercially attractive or with a higher uptake in EV adoption. This however creates a cycle whereby charging infrastructure is concentrated in particular locations and missing in others [2]. In addition, access to EV charging is not consistent across the population, where minorities and households with lower incomes are underserved. These issues have been observed in different countries such as the UK [9] and United States [10], [11]. The problem is exacerbated when areas of deprivation exhibiting severe inequalities in charger placement are considered—as identified in studies carried out in Glasgow and Edinburgh in Scotland, UK [12].

Studies in the literature have developed metrics considering population attributes (e.g. education, age, income) to assess spatial disparity in the access to public EV charging infrastructure. For instance, [13] reports spatial disparities in Hong Kong. A similar approach was applied in [9] to London, UK, but in the methodology accessibility was combined with levels of fuel poverty and proportion of Black, Asian and Ethnic Minority populations of Lower Super Output Areas (LSOAs)—thus increasing the analytical complexity of the method.

Despite the growing evidence of inequality access of EV charging infrastructure in the UK, this constitutes an under-researched area where quantitative accessibility

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metrics are still missing—particularly within a Welsh context. The South East Wales region comprises a compelling case study area, with its post-industrial mining communities settled in the Valleys, and exhibiting a historically low EV charging infrastructure deployment. The region has a wide range of deprivation, as indicated by the Welsh Index of Multiple Deprivation (WIMD) [14]. This is a relevant attribute, as previous work based in Scotland, for which the Scottish Index of Multiple Deprivation (SIMD) was employed, shows that geo-demographics can help predict access to charging infrastructure [12]. In addition, South East Wales features different types of communities, ranging from urban to rural [15].

Using the WIMD and the geographical classification of LSOAs can lay the groundwork for investment and policy opportunities in Wales. To this end, this paper presents a methodology to assess the accessibility to EV charging infrastructure in South East Wales—aimed to identify the area's most at need to improve access to public charging. The framework is based on a Gaussian Two-Step Floating Catchment Area (G2SFCA) at an LSOA level to assess spatial accessibility. The approach integrates the WIMD and classifies areas according to the Rural-Urban Classification in [15], which constitute innovative contributions. K-means clustering is used to identify the main areas of focus for improved spatial planning of public EV charging. This was done to address the urban-to-rural divide, and such an approach helps identifying where interventions are most needed.

2. STUDY AREA: GEOGRAPHY AND SOCIOECONOMIC DEMOGRAPHICS

The region of South East Wales was selected due to its diverse geography, which includes the South Wales Valleys and their diverse areas of deprivation. The region also has a good mix of rural and urban areas including the city of Cardiff (which is the capital of Wales). Many of the communities in the Valleys are mining communities with no access to off-street parking. Thus, EV owners would have a greater reliance on public charging infrastructure.

An LSOA is a small bounded geographical area with a population of 1,000 to 3,000 people [16]. This population bound means that LSOAs in South East Wales can differ significantly depending on population density, with rural LSOAs covering considerably larger zones than densely populated LSOAs (e.g. city-based).

The LSOA regions are shown with their respective WIMD quantile ranges in Fig. 1, which clearly shows the deprived Valley regions located in the north of the map.

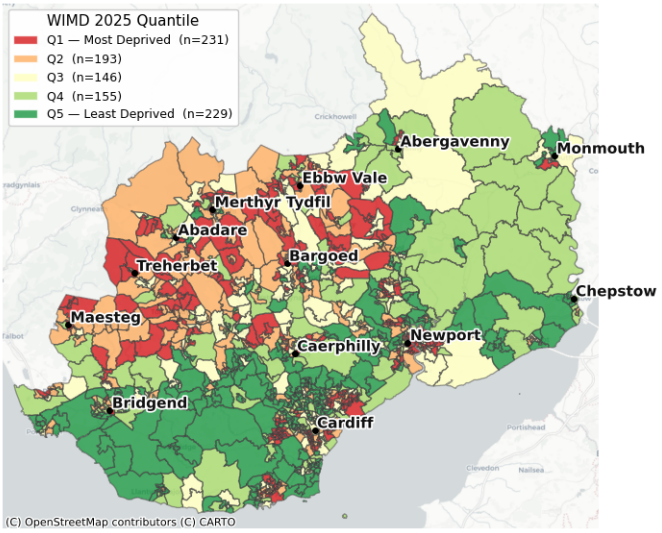

Fig. 1 WIMD Quantile Map.

3. METHODS

3.1 LSOA Centroids

LSOA centroids are required to define a distance metric to quantify EV charger accessibility. This is because the geometric centre in rural or Valleys-based LSOAs might not represent where most of the population resides. Centroids were calculated in this paper using the mean location of domestic dwellings within the LSOA.

3.2 Charger Accessibility

Scores for EV charging infrastructure accessibility are calculated using the approach presented in [13]. These dimensionless scores use the G2SFCA approach to calculate the ratio of supply and demand of EV chargers to population within a 5 km radius of each LSOA and EV charger station. A Gaussian decay function is applied to the ratio of supply and demand to allocate higher weights to EV charger stations located nearby. A 5 km radius is the Euclidean distance from the LSOA centroid and the charger station and was chosen to approximately represent a 10-minute drive.

The accessibility score A_i is calculated with

$$A_i = \sum_{j\epsilon\{d_{i,j},d_o\}} R_j \times H\left(d_{i,j}, d_0\right) \quad (1)$$

where R_j is the ratio of supply and demand, $H\left(d_{i,j}, d_0\right)$ is the Gaussian decay function, d is the distance between the LSOA centroid and the EV charging station, d_o is the catchment radius (in this case of 5 km) and j is an index to identify the charger station.

R_j in (1) is obtained with

$$R_j = \frac{S_j}{\sum_{k\epsilon\{d_{i,j}\leq d_0\}} p_k H(d_{i,j}, d_0)} \quad (2)$$

where S_j is the total supply of EV chargers at charger station j, p_k is the population of an LSOA within the catchment radius d_o, and k is the LSOA in the EV charger catchment zone.

H in (1) and (2) is described by

$$H(d, d_o) = \begin{cases} \dfrac{e^{-\frac{1}{2}\left(\frac{d}{d_0}\right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}} & \text{if } d \leq d_0 \\ 0 & \text{if } d \geq d_0 \end{cases} \quad (3)$$

As shown by (3), H is a function of the distance d between the LSOA centroid and the EV charging station, and the catchment radius d_o. Any LSOA centroids and EV chargers that are separated by a distance greater than $d_o = 5\,\text{km}$ are assigned a weight of zero and do not contribute to the accessibility scores A_i.

3.3 Gini Index

The Gini index (or Gini coefficient) was adopted to assess the disparity in access to EV charging infrastructure [17]. It ranges from 0, indicating perfect equitable access to EV charging infrastructure across the population of study, to 1, representing maximum inequality. The Gini index was calculated for each LSOA within South East Wales. It is defined by

$$G = 1 - \sum_{i\epsilon I} (A_{i+1} + A_i)(p_{i-1} - p_i) \quad (4)$$

$$G^m = 1 - \sum_{i\epsilon I} (A_{i+1} + A_i)(p_{i+1}^m - p_i^m) \quad (5)$$

where i identifies a given LSOA within the total LSOAs I in the study region, A_i are the accessibility scores calculated from (1), and p is the population for each LSOA. A total population Gini index is calculated using (4), or for each sub-category m using (5).

3.4 Moran's I

Moran's I is used to measure spatial autocorrelation [18]. In this work, it indicates where there are clusters of low or high access to EV charging infrastructure between the LSOAs of the study area, forming spatial hotspots and cold spots for EV charging access. There are four categories, which are shown in Table 1.

Table 1 Moran's I classification

Classification	Local Access	Neighbouring Access
High-High	High	High
High-Low	High	Low
Low-High	Low	High
Low-Low	Low	Low

3.5 K-Means Clustering

Within the context of this work, K-means clustering [19] helps identifying where areas (or clusters) are well-served and where there is disparity in the access to EV charging infrastructure. The clustering was completed based on the accessibility scores, WIMD rank and rural/ urban classification categories.

The number of clusters selected was quantitively determined by conducting an 'elbow and silhouette' analysis [20], with $k = 4$ giving the peak silhouette, and an inertia decrease with increasing values of k beyond 4.

4. RESULTS AND DISCUSSION

4.1 Accessibility Scores

The accessibility scores for South East Wales are shown in Fig. 2. These results show large areas of low charger accessibility with smaller pockets of increased accessibility, and increased charge deployment around population centres.

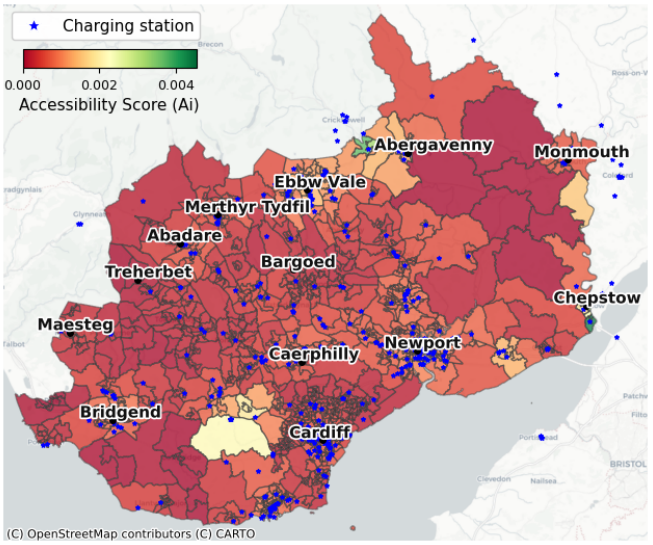

Fig. 2 Accessibility scores for LSOAs in South East Wales and public EV charger location.

WIMD quantile analysis was conducted and showed that there was little significance of access across the WIMD rankings within the study area. This is indicated in Table 2.

Table 2 Mean accessibility scores per WIMD ranking quantile.

Quantile	Mean A_i	No. of LSOAs
1	0.000463	231
2	0.000420	193
3	0.000525	146
4	0.000576	155
5	0.000451	229

The results presented in this section are inconsistent with those reported in [10], [11], [12], which link deprivation to accessibility of EV charging infrastructure. For South East Wales, other factors are more likely to influence access instead. In addition, the results show no statistical significance between WIMD quantiles, with a Kruskal-Wallis index of $p = 0.171$, which tests if there is a statistical difference between the quantile groups. This does not mean there is an absence of inequality issues, but that geographic factors constitute the primary reason for inequality—as discussed in the next sections.

4.2 Gini Index, Rural Urban Classification

The accessibility scores shown in Fig. 2 are used to calculate the Gini indices, which allow for a clear differentiation of the disparity of allocation of public EV chargers. The Lorenz curves and Gini index for South East Wales are shown in Fig. 3. The global population Gini index is $G = 0.3525$, which indicates a moderate inequality of access across the region. Compared to the results reported in [13], the results in this paper imply that South East Wales has better access to public EV charging infrastructure than Hong Kong [13].

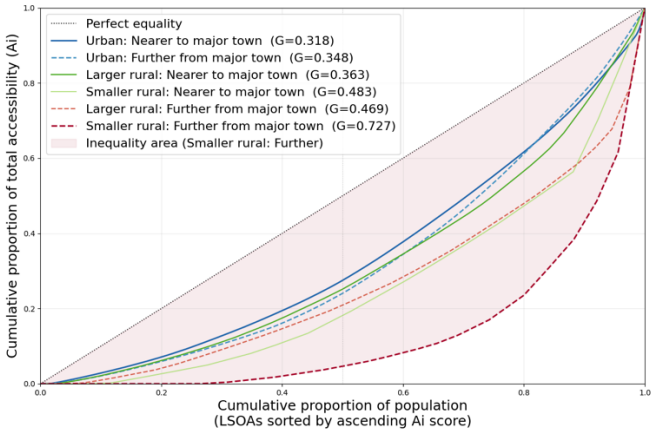

Fig. 3 Lorenz curves and Gini index for LSOA Rural-Urban classification.

The Lorenz curves in Fig. 3 show how equally distributed EV charging infrastructure is spread out across the population.

4.3 Global and Local Moran's I

The spatial context of EV accessibility is required to understand the smaller regional differences across the region of study. Fig. 4 shows the spatial autocorrelation of public EV charger accessibility scores.

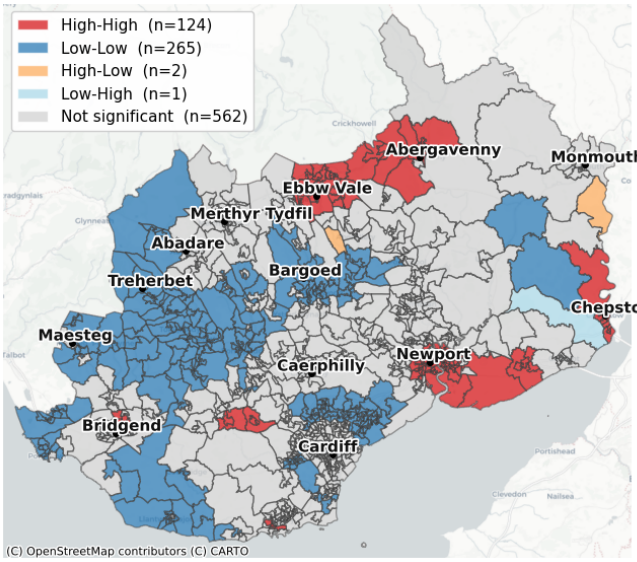

Fig. 4 Moran's I spatial autocorrelation of public EV charger accessibility scores.

The results shown in Fig. 4 evidence significant areas with high access to public EV charging within the LSOA and neighbouring areas. There is a significant number of LSOAs, 265 in total, with low access to public EV chargers and their surrounding area. A global Moran's I of 0.7595, with a probability $p = 0.001$, indicates a strong positive spatial autocorrelation, showing there are both clusters of high EV charging accessibility and clusters of low EV charging accessibility.

4.4 K-Means Clustering

To improve the planning process in EV charging infrastructure deployment, cofactors including deprivation and rural/urban classification need to be considered to improve visibility of accessibility in the region. The four clusters identified within the study are shown in Fig. 5.

As evidenced in Fig. 5, the four distinct cluster types require different types of interventions to tackle the EV charger divide. A well-served cluster exhibits the best accessibility overall. Underserved urban communities are split into affluent and deprived, while the final cluster is rural isolated.

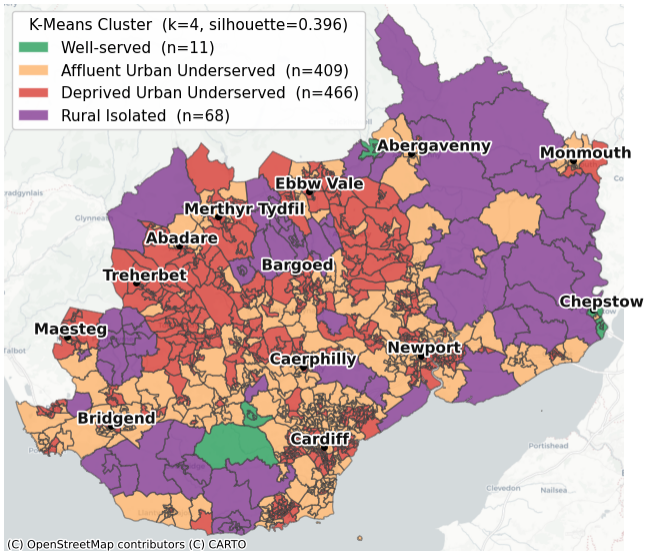

Fig. 5 K-Means clustering of public EV charging infrastructure.

The silhouette value of 0.396 represents a weak-to-moderate clustering. This is due to the use of the WIMD ranking, which is a continuous metric ranked from highest to lowest.

The key cluster characteristics are summarised in Table 3. These show that each cluster has distinct features: urban underserved clusters are split by the mean WIMD rank, the rural isolated cluster has zero public EV charger accessibility and is 100% rural, and the well-served cluster has the highest accessibility scores.

Table 3 Cluster profile summary

Cluster	Mean WIMD Rank	Mean A_i	Rural %
Well-Served	1,452	0.003	45.5
Affluent Urban-Underserved	1,498	0.001	6.4
Deprived Urban-Underserved	435	0.001	4.1
Rural Isolated	985	0.000	100

4.5 Limitations and Further Work

The G2SFCA approach adopted in this paper to calculate accessibility scores is based on the Euclidian distances between LSOA centroids and EV charger stations. Future work could consider road data and driving distances to better complement the geographic features of the Valleys within South East Wales.

The results presented in the paper focus on the diverse area of South Wales with its mining communities, rural and urban areas and geography of the Valleys. The methodology could be extended to the whole of Wales and the rest of the UK, but this falls out of the scope of this paper and represents future work.

5. CONCLUSIONS

Equitable access to public EV charging infrastructure is essential for renewable transport uptake in Wales and to reach Net Zero targets. To contribute to these efforts, this paper investigated, through statistical methods, the contributing factors leading to inequality of public EV charging access in South East Wales.

Previous studies have demonstrated that socio-demographic factors are clear indicators of accessibility inequality. However, the geographic differences in South East Wales, and particularly in the Valleys, show a stronger relationship to a rural/urban divide. Specifically, the region's topology is the largest differentiator in access, with small rural areas away from towns having the worst access to charging infrastructure.

Classification of LSOAs was achieved by applying K-means clustering to the geographical data and using deprivation and accessibility indices. This approach can be generalised and adopted nationally or internationally if these data are readily available. In addition, the rural/urban classification can be directly used, or proxy measures (e.g. population density) could be used instead if this metric is unavailable.

The approach presented in the paper can support policymakers in improving investment and targeted interventions into low accessibility areas of EV charging infrastructure. In Wales, underserved areas could be targeted with tailored schemes to tackle the charging divide. For instance, rural isolated areas would require significant new infrastructure due to the severe lack of access. At the same time, strategies towards improving access in urban areas would differ, with the most deprived areas potentially requiring public support from local governments to assist in the infrastructure rollout. More affluent areas could rely on markets and private investment instead.

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