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GIS-based geospatial analysis for identifying optimal locations of residential on-street electric vehicle charging points in Birmingham, UK

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ABSTRACT

Global urbanization and the growing need for sustainable transportation solutions are increasing the demand for electric vehicle (EV) infrastructure. This research aims to identify optimal locations for Residential On-Street Electric Vehicle Charging Points (RO-EVCPs) that are essential for residents without access to off-street parking and to support the transition to a sustainable urban environment in Birmingham. A GIS-based model, incorporating key location criteria such as accessibility, environmental impact, and infrastructure compatibility, can effectively identify suitable locations for RO-EVCP deployment, improving access and inclusivity for electric mobility. The study develops a customized geographic information systems (GIS) model, utilizing the Analytic Hierarchy Process (AHP) for weighting location criteria, with validation through geospatial tools like Google Earth® and Street View. The model generates a spatial suitability map, categorizing areas into optimal, moderate, and limited suitability for EV charging, with an emphasis on accessibility, environmental impact, and inclusiveness. High-priority streets and recommended charging point numbers are identified. The findings emphasize accessibility and inclusiveness, crucial for individuals without off-street parking, promoting an equitable transition to electric mobility. This research contributes to sustainable urban mobility planning by advocating data-driven decision-making in EV infrastructure development, aligning with climate change mitigation objectives.

1. Introduction

The rapid growth of the population and increasing urbanization trend have led to detrimental environmental such as global warming and climate change (Abid et al., 2022; Wang & Cheng, 2020). In response to these challenges, Electric vehicles (EVs) are introduced as a solution to clean energy and toward achieving sustainable cities, and nowadays, this type of new mobility has been growing rapidly worldwide (Liang et al., 2019). EVs have been growing rapidly worldwide due to their ability to reduce greenhouse gas emissions, mitigate climate change, and improve air quality and noise pollution (Hajiaghaei-Keshteli et al., 2023; Karolemeas et al., 2021). One of the most significant urban challenges for EVs is providing a charging infrastructure. Electric Vehicles Charging Station (EVCS) should also be widespread and available for everyone to ensure equity, also accessibility for all members of the community to promote fairness and inclusivity (Charly et al., 2023; Iravani, 2022). Poor location of charging stations can lead to waste of resources and negatively impact decarbonisation efforts (Ademulegun et al., 2022).

This study focuses on the city of Birmingham, UK, selected as a representative case to explore the optimal location of Residential On-Street Electric Vehicle Charging Points (EVCPs) in urban areas where off-street parking is limited. Projections indicate that by 2030, Birmingham will have over 170,000 electric vehicles on its roads, necessitating the installation of approximately 3630 public charging points, including 1375 dedicated Residential On-Street Charging Points (Hahmann et al., 2011). Recent data highlight that around 75 % of EV charging occurs at home, predominantly overnight, underscoring the urgency to address the charging needs of residents without private parking (Department for Transport, 2022a). The lack of off-street parking spaces mostly impacts urban and city regions, particularly social housing inhabitants, as many households lack access (Ministry of Housing, Communities & Local Government, 2019). Most EV users use home charging, however, the lack of private parking infrastructure makes it difficult for these residents to do so. Accessibility and the

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unequal distribution of public charging facilities across the country restrict EV adoption in this demographic (AA Populus Driver Poll Summaries, 2020; Department for Transport, 2022c). On-street EV charging's significance lies in its convenience and alignment with established driving and parking behaviors, with near-home charging being the top choice for future EV charging. Charging device location categories are determined by factors such as their physical location, the type of facility they are situated in, accessibility, and the specific charging services they provide. On-street charging refers to the installation of charge points along the roadside, often integrated into lampposts or bollards, as well as in local residential parking areas. This charging option primarily serves individuals without access to off-street parking. These charge points offer slow or fast charging capabilities and can be utilised overnight, mirroring the convenience of home charging (Frade et al., 2011; CMA, 2021; Department for Transport, 2023a).

Previouse studies have employed various approaches to determine optimal EVCS locations, including multi-criteria analysis and optimization models Grote et al. (2019); Mahdy et al. (2022); Charly et al. (2023). These investigations have primarily centered on factors such as road access, parking availability, population density, and existing infrastructure (Campbell et al. (2012); Namdeo et al. (2014)). Nevertheless, there remains a notable gap in the literature regarding the examination of residential on-street charging locations that also consider demographic factors and environmental indicators, which this research aims to address.

This research introduces a novel approach, leveraging Geographic Information Systems (GIS) and geospatial analysis, to identify optimal locations for Residential On-Street EV Charging Points (EVCPs). It incorporates previously unaddressed factors such as 'Inclusive EVCP Distribution for Disabilities,' 'Noise Pollution,' 'EV-Prone Age Groups,' and 'Air Quality Levels.' The primary contribution of this study is the introduction of criteria like 'Inclusive EVCP Distribution for Disabilities' and 'Noise Pollution,' which have not been considered in previous research on charging infrastructure—whether for destination, en-route, or on-street charging. Moreover, this study is the first to explore 'EV-Prone Age Groups' and 'Air Quality Levels' specifically in the context of Residential On-Street Charging Points.

By doing so, it aims to enhance the existing charging infrastructure, ensuring it aligns with the demographic and environmental landscape of Birmingham. The dual objectives of this study are to reduce carbon emissions and promote social inclusivity, which resonate with Birmingham's sustainability goals for a cleaner, healthier urban environment. The development of a tailored GIS-based model facilitates precise location identification for EVCPs, ensuring accessibility for all community members, especially marginalized groups, while addressing environmental concerns and enhancing air quality. This comprehensive approach aims to contribute evidence-based recommendations for the deployment of Residential On-Street EV charging points, forming a strategic framework that guides Birmingham toward a more sustainable and electrified future.

The paper is organized as follows: Section 2 reviews the relevant literature on EVCS location methodologies and outlines the study's objectives. Section 3 presents the data sources and study area. Section 4 details the methodology employed in site selection. Sections 5 and 6 discuss the analysis, results, and implications, culminating in conclusions drawn from the research findings.

2. Literature review

2.1. Recent research in optimizing electric vehicle charging station locations (EVCs)

The development of public electric vehicle (PEV) charging infrastructure has attracted considerable research interest in recent times. Numerous studies have endeavored to pinpoint appropriate locations for both public and residential charging points (CPs) in diverse geographic regions. In the pursuit of optimal locations for electric vehicle (EV) charging stations, various research studies have contributed significantly to this endeavor. Kadri et al. (2020) utilised a combination of stochastic programming and Genetic Algorithms to tackle the challenge of locating fast charging stations. Zhu et al. (2016) presented a mathematical model paired with Genetic Algorithms to address the deployment of plug-in charging stations. Their research aimed to reduce ownership costs for EV users and alleviate range anxiety. Through their approach, they successfully optimized the placement of plug-in charging stations, ensuring cost-effectiveness in their deployment. Xi et al. (2013) approached the problem of public charging station placement, with a focus on cost-effectiveness. They employed simulation-optimization techniques to identify optimal locations for public charging stations while considering factors such as private EV use and charger cost-effectiveness. Huang and Kockelman (2020) utilised genetic algorithms to optimize the placement of fast-charging stations. Their approach factored in various considerations, including cost, equipment, and network congestion feedback, resulting in an efficient placement strategy.

In addition, Rane et al. (2023) evaluated the suitability of zones for electric car vehicle charging stations by integrating the GIS, MIF, and TOPSIS approaches. This research identified optimal locations through a weighted overlay analysis integrating thirteen influencing factors. In order to examine the spatial patterns of Charging Demand Indicators (CDI) and their correlation with the distribution of Public Charging Stations (PCS), Kang, Kong et al. (2022) used spatial regression modeling and kernel density functions. The results demonstrated significant variations in the demand for charging EVs over various urban structures, weekdays versus weekends, and EV travel distances.

Bayram et al. (2022) conducted a spatial analysis to enhance the placement of fast-charging stations in urban areas. By leveraging Geographic Information System (GIS) and linear programming, they optimized fast charger placement based on population and road traffic data. This research demonstrated the potential to significantly improve EV coverage in urban environments, particularly in cities where such research is limited. In addition to these specific studies, a range of methodologies has been employed for optimal charging station placement. A variety of Multi-Criteria Decision Making (MCDM) techniques have been utilised in this context, each offering unique approaches to the challenge of optimal charging station placement. Some of these techniques include the Analytical Hierarchy Process (AHP), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Preference Ranking Optimization Method for Enrichment Evaluation (PROMETHEE), among several others.

The applications of these techniques are diverse, spanning fuzzy AHP in Ankara, Turkey (Erbaş et al., 2018), fuzzy TOPSIS in Beijing, China (Guo & Zhao, 2015), and GIS-based MCDM methods in Istanbul (Kaya et al., 2020), to name a few. These approaches have been instrumental in optimizing the selection of suitable EV charging station locations, ensuring a comprehensive assessment of various criteria and factors. Furthermore, research studies have explored alternative methodologies such as Bayesian networks (Hosseini & Sarder, 2019), k-means clustering (Zhang et al., 2019), mixed-integer optimization models (Frade et al., 2011), and machine learning techniques (Roy & Law, 2022) to tackle the complexities of EV charging station placement. These studies have expanded our understanding of how different methodologies can be applied to address site selection challenges and promote the effective deployment of charging infrastructure. In summary, the body of literature on EV charging station site selection encompasses a wide array of methodologies, each offering unique insights and approaches to optimize the placement of these crucial infrastructure elements. These studies collectively contribute to the ongoing effort to establish a robust and efficient EV charging network, essential for the widespread adoption of electric vehicles.

2.2. Recent research in optimising on-street electric vehicle charging point locations (EVCPs)

Grote et al. (2019) introduced a practical approach tailored to the needs of Local Government Authorities (LGAs) for the identification of suitable streets in Southampton, UK, where on-street Plug-in Electric Vehicle (PEV) charging infrastructure could be effectively deployed. This approach hinged on the utilisation of Geographic Information System (GIS) analysis, alongside readily available census and parking data. As a result of their study, Grote et al. (2019) were able to provide LGAs with a set of 128 recommended streets, offering a valuable blueprint for the improvement of residential charging infrastructure. Additionally, the works of Campbell et al. (2012) and Namdeo et al. (2014) emphasized the significance of comprehending the demographic profiles and characteristics of potential early adopters of Plug-in Electric Vehicles (PEVs). These studies stressed the importance of assessing the demands for charging infrastructure by considering socio-economic data and user-specific attributes. In a related vein, Lin and Greene (2011) put forward a recommendation that advocated for a clear differentiation between public and residential charging points. Their work highlighted the necessity of tailoring charging infrastructure to cater to the distinct needs and preferences of these diverse user groups.

In their study, Mahdy et al. (2022) utilised a multi-criteria decision-making approach, which involved the integration of the Analytical Hierarchy Process (AHP) with Geographic Information System (GIS) analysis. In their comprehensive analysis, researchers considered a variety of factors to determine the ideal locations for on-road Electric Vehicle (EV) charging points within the Winchester District, UK. These factors encompassed road classifications, ease of road access, the presence of on-road parking spaces, road gradients, proximity to fuel stations, the availability of current/planned charging facilities, parking provisions for cars, and the distribution of the local population. Their research underscored the critical role played by both spatial and demographic analyses in the process of optimizing charging infrastructure within specific geographical regions.

Collet et al. (2022) addressed the challenge of providing EV charging accessibility to residents without off-street parking in Oxford, utilising geospatial analysis with the GECCO tool to identify suitable car parks. This approach offers a practical strategy for local authorities and charge point installation companies to meet increasing EV charging demand and contribute to sustainability goals. Charly et al. (2023) explored the strategic placement of EVCPs in urban areas, focusing on Dublin, Ireland. Their GIS-based methodology categorised charging infrastructure into en-route, shared-residential and destination charging types. Factors like population density, parking availability, proximity to existing charging stations, and accessibility to key locations were considered. The study identified 770 high-priority EVCP locations for installation by 2025 and 3080 medium-priority sites for deployment by 2030 in alignment with Dublin's EV charging goals. However, the study does not consider judgment criteria or stakeholder preferences, focusing instead on A hands-on spatial analysis using GIS techniques. It also has limitations related to data sources and infrastructure considerations. Its transferable approach, based on QGIS and open-source data, can serve as a model for similar spatial problem-solving in other regions.

By the year 2050, it is anticipated that approximately 10 million electric cars and vans will be regularly parked on residential streets in the UK overnight, necessitating accessible and reliable charging solutions (Department for Science, Innovation & Technology, 2023). Existing research indicates that most EV owners prefer home charging over public or workplace options during the night, leading to a focus on public charging station placement in the literature (Bjerkan et al., 2016; Mohamed et al., 2016; Sierzchula et al., 2014; Silvia & Krause, 2016). However, there remains a gap in strategically placing Residential On-Street EV Charging Points, particularly in urban areas. Birmingham, UK, is a typical example, which is taken as a test case.

This research addresses these gaps by introducing previously unexplored criteria, such as 'Inclusive EVCPs Distribution for Disabilities' and 'Noise Pollution,' alongside factors like 'EV-Prone Age Groups' and 'Air Quality Levels.' These innovative factors will guide the geospatial analysis and classification of Residential On-Street EV Charging Points in Birmingham, UK. The exclusion and inclusion criteria presented in this research offer a novel approach to optimizing EV charging infrastructure placement, ensuring that it meets the needs of diverse user groups while also minimizing environmental impact.

By integrating these additional criteria, this study provides new insights into the strategic placement of EV charging points, emphasizing accessibility, inclusivity, and environmental sustainability—areas that have not been sufficiently considered in prior studies. This will help shape the future of residential on-street EV charging infrastructure in a more holistic and socially responsible manner.

- How can the inclusion of accessibility criteria, such as EV charging points for users with disabilities, impact the strategic placement of Residential On-Street EV Charging Points in urban areas?
- What role do environmental factors, such as noise pollution and air quality levels, play in the optimal placement of residential on-street charging infrastructure?
- How do demographic factors, particularly the distribution of EV-prone age groups, influence the spatial planning of Residential On-Street EV Charging Points in urban areas?
- Can a dual classification approach (involving both exclusion and inclusion criteria) provide a more comprehensive framework for selecting optimal locations for Residential On-Street EV Charging Points, considering both accessibility and environmental sustainability?

This research seeks to address these questions by offering a comprehensive geospatial analysis of Residential On-Street EV Charging Infrastructure in Birmingham, UK, incorporating a novel set of criteria that expands upon traditional approaches. By introducing and integrating inclusivity and environmental considerations into EV charging infrastructure planning, this study aims to contribute to the development of a more sustainable and equitable urban mobility network.

3. Materials and data

3.1. Study area

Birmingham, situated inland on the Birmingham Plateau in the central part of Great Britain, and operates as a critical hub in the heart of the country and is governed by the Birmingham City Council. With its strategic geographic location, ongoing population growth, and regional importance, Birmingham continues to play a vital role within the broader landscape of the United Kingdom (Population of Birmingham, 2023). Birmingham currently has around 240 charge points, with over 140 chargers in the city. Most are in the city center, with some along major roads. Many are fast chargers, and there are also some rapid and ultra-rapid chargers available (Birmingham City Council, 2021a). Birmingham's city-wide EV charge point strategy, stretching until 2032, differs significantly from its initial phase (Fig. 1).

3.2. Exploring key criteria for optimal residential on-street EV charging point locations

This study focuses on strategically placing electric vehicle charging points (EVCPs), particularly in on-street residential areas, considering various influential factors. It adheres to UK Government and Birmingham City Council guidelines, including the Net Zero Strategy, Take Charge: Electric Vehicle Infrastructure Strategy, and Birmingham's Electric Vehicle Charging Strategy. The study recognizes the impact of household income on EV purchase decisions and emphasizes equitable

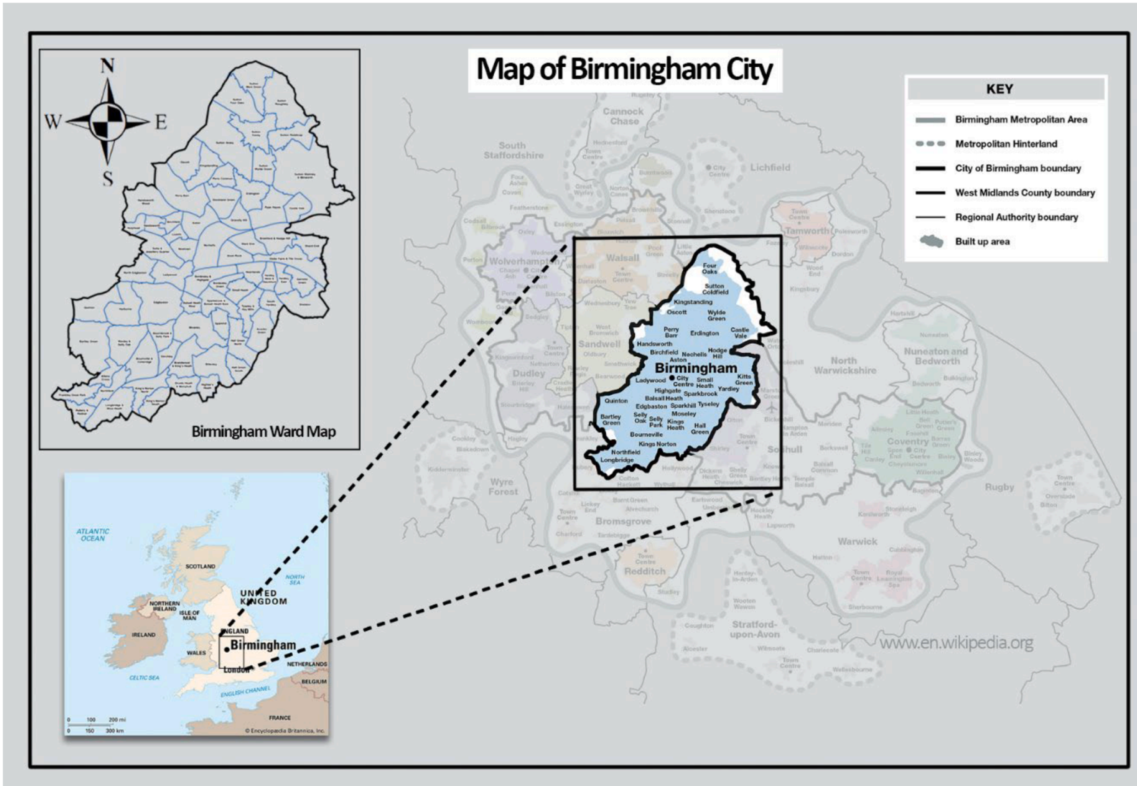

Fig. 1. Map of Birmingham city council areas and wards in the study area.

access to charging infrastructure, aiming to avoid concentration in affluent areas. Unlike previous research that considered factors like lamp post proximity and income, this study deliberately excludes such criteria to ensure fair access for all users.

This study employs a selection of criteria previously employed in related research, aligning with the study's subject and geographic scope. Furthermore, it introduces novel criteria, thereby expanding the array of factors and individuals being considered. This study adopts a dual classification approach for its site-selection criteria. The initial category comprises exclusion criteria designed to exclude unsuitable locations outside the study's scope. These criteria encompass road type, road speed, road slope, feasibility of on-street parking, and potential locations for non-residential On-Street charging. The second category encompasses suitability criteria for the selection of optimal charging point sites. These criteria are further grouped into three distinct categories: Accessibility and Infrastructure, Population Distribution, and Environmental and Geographical Factors. Additionally, they are subdivided into eight sub-criteria, including Residential Proximity, Distance to Available EVCPs, Population Density, Inclusive EVCPs Distribution for Disabilities, EV-Prone Age Groups, Air Quality Level, Noise Pollution, and Road Slope Compatibility. Further details, reasons for inclusion, and relevant literature references for these criteria are provided below and concisely summarized in Table 1.

4. Methodology

The research methodology is a multifaceted and data-driven process designed to achieve research objectives systematically. It encompasses several key stages, each contributing to the comprehensive analysis of optimal RO-EVCP locations (see Fig. 2).

4.1. Literature review

The research begins with an extensive literature review, adopting a deductive approach. This review explores existing theories and knowledge related to electric vehicle infrastructure planning and identifies gaps in the literature. By building upon established research, the study contextualizes its analysis within the broader field of sustainable urban mobility.

4.2. Identification of influential factors

The next crucial step in the research process involves the identification of influential factors. This phase is dedicated to pinpointing the key elements that significantly impact the selection of optimal RO-EVCP locations. Through an exhaustive review of existing literature and expert consultations, these factors will be meticulously curated to serve as the foundational criteria guiding the study's decision-making process.

4.3. Data collection

To support the analysis, the research collects diverse datasets relevant to Birmingham, UK, from credible sources. These datasets include demographic information, environmental data, road network details, and geographic data. Table 2, provides a comprehensive summary of the data sources and attributes used in the analysis.

4.4. Suitability models

The core of the methodological approach involves developing suitability models. This process combines the Analytic Hierarchy Process (AHP) with Geographic Information Systems (GIS) within a Geographic Information Systems Multi-Criteria Decision Analysis (GIS-MCDA) framework. In this step, AHP is employed, beginning with pairwise comparisons through expert surveys that are normalized to ensure consistency, ultimately assigning weightings to the identified criteria based on their relative importance. The GIS-MCDA framework integrates these weighted criteria to create suitability models, categorising

Table 1
Criteria description and studies that have used them for EVCSs and EVCPs.

Criteria		Reason for consideration	EVCP location studies that have used this criteration
Suitability Criteria			
SCI.I	Residential Proximity	To enhance residential charging, should be placed chargers closer to homes; distant households use overnight chargers less due to inconvenience (Gilbert et al., 2020).	(Charly et al., 2023; Karolemeas et al., 2021; Pagani et al., 2019)
SCl.2	Distance to Available EVCPs	To maximize coverage and accessibility, new charging stations should be positioned at a distance from existing ones.	(Lee et al., 2021; Carra et al., 2022; Csiszár et al., 2019; Kaya et al., 2020; Raposo et al., 2015; Mahdy et al., 2022; Erbas et al., 2018)
SC2.l	Population Density	Research using census data to explore the distribution of individuals capable of adopting electric vehicles verifies this pattern (Campbell et al., 2012). In densely populated areas, residents often lack private driveways and home charging options, In de making them reliant on public charging infrastructure (Gilbert et al., 2020 ; Schmidt et al., 2020).	(Awasthi et al., 2017; Campbell et al., 2012; Carra et al., 2022; Charly et al., 2023; Csiszár et al., 2019; Erbaş et al., 2018; Frade et al., 2011; Guler & Yomralioglu, 2020; Iravani, 2022; Ju et al., 2019; Karolemeas et al., 2021; Kaya et al., 2020; Mahdy et al., 2022; Raposo et al., 2015; Roy & Law, 2022; Wu et al., 2016; Zhao & Li, 2016)
SC2.2	EV-Prone Age Groups	EV-Prone Age Groups typically encompass younger demographics with a greater interest in electric vehicles and electric mobility (Department for Transport, 2017).	(Costa et al., 2017; Lee et al., 2021; Pagani et al., 2019)
SC3.l	Air Quality Level	Areas with poor air quality may prioritize EVCPs to encourage cleaner transportation options.	(Guo & Zhao, 2015; Hosseini & Sarder, 2019; Kaya et al., 2020; Lee et al., 2021; Zhao & Li, 2016)
SC3.2	Noise Pollution	Placing EVCPs in noisy urban areas can help reduce traffic noise pollution (Campbell et al., 2012; Manzetti & Mariasiu, 2015).	*NIA*
SC3.3	Road Slope Compatibility (≤10 %)	To optimize the placement of EVCPs, it is essential to identify flat areas with slopes less than 10 %. The evaluation process focuses on roads meeting this criterion (Streets And Transport In the Urban Environment (CIHT, 2023)).	(Costa et al., 2017; Erbaş et al., 2018; Guler & Yomralioglu, 2020; Kaya et al., 2020; Mahdy et al., 2022; Zhang, Zhang, Farnoosh, Chen & Li, 2019)
Exclusion Criteria			
ExCl	Road Speed	To ensure safety and compliance with the Highway Code's rule 249, roads with speed limits exceeding 30 mph should be excluded (The Highway Code – Waiting and parking (238 to 252), GOV.UK).	(Karolemeas et al., 2021; Mahdy et al., 2022)
ExC2	Road Type	Exclude non-residential roads to optimise EVCPs placement near residential areas.	(Costa et al., 2017; Karolemeas et al., 2021; Mahdy et al., 2022)
ExC3	Potential Public Services Locations for Non-Residential On-Street Charging	To ensure a fair distribution of residential on-street EVCPs, it is advisable to exclude parking spaces in areas with high travel attraction rates and extended parking durations, which are better suited for non-residential on-street charging.	(Charly et al., 2023; Guler & Yomralioglu, 2020; He et al., 2018; Iravani, 2022; Karolemeas et al., 2021; Kaya et al., 2020; Mahdy et al., 2022; Raposo et al., 2015).
ExC4	Road Slope (>10 %)	To enhance energy efficiency and safety, roads with slopes exceeding 100/o should be excluded from consideration.	(Costa et al., 2017; Erbaş et al., 2018; Guler & Yomralioglu, 2020; Kaya et al., 2020; Mahdy et al., 2022; Zhang et al., 2019).
ExC5	Feasibility of On-Street Parking	Adequate on-street parking is crucial for choosing the best residential EVCPs, especially for overnight charging convenience.	(Janjić et al., 2021; Carra et al., 2022; Charly et al., 2023; Karolemeas et al., 2021; Kaya et al., 2020; Mahdy et al., 2022)

potential RO-EVCP locations into three classes: Limited Suitability, Moderate Suitability, and Optimal Suitability, represented by ratings from 1 to 3.

4.5. Criteria categorisation

The criteria used in the analysis are organized into three distinct sections. Initially, these criteria function as exclusionary factors, allowing for the removal of unsuitable data, subjects, or elements from consideration. Subsequently, they transition into suitability criteria, facilitating the assessment of location appropriateness for specific purposes. Finally, the criterion of on-street parking feasibility becomes essential, contributing to visual validation and the definitive selection of optimal EV charging point locations.

4.6. Visual validation

To validate the suitability models and ensure real-world feasibility, the research employs visual validation techniques. This step entails physically inspecting and verifying the selected RO-EVCP locations using tools such as Google Earth® and Google Street View.

4.7. Applying analytic hierarchy process (AHP) for optimal EV charging point location analysis

The Analytic Hierarchy Process (AHP) is a widely used mathematical method and decision-making tool renowned for its simplicity, flexibility, and ability to assess criteria consistency . Its application in selecting optimal locations, particularly within Geographic Information Systems (GIS), is well-documented in the (Janjić et al., 2021; Bitencourt et al., 2021; Erbaş et al., 2018; Karolemeas et al., 2021; Lee et al., 2021; Skaloumpakas et al., 2022). Through pairwise comparisons, AHP facilitates the determination of factor weights, enabling decision-makers to

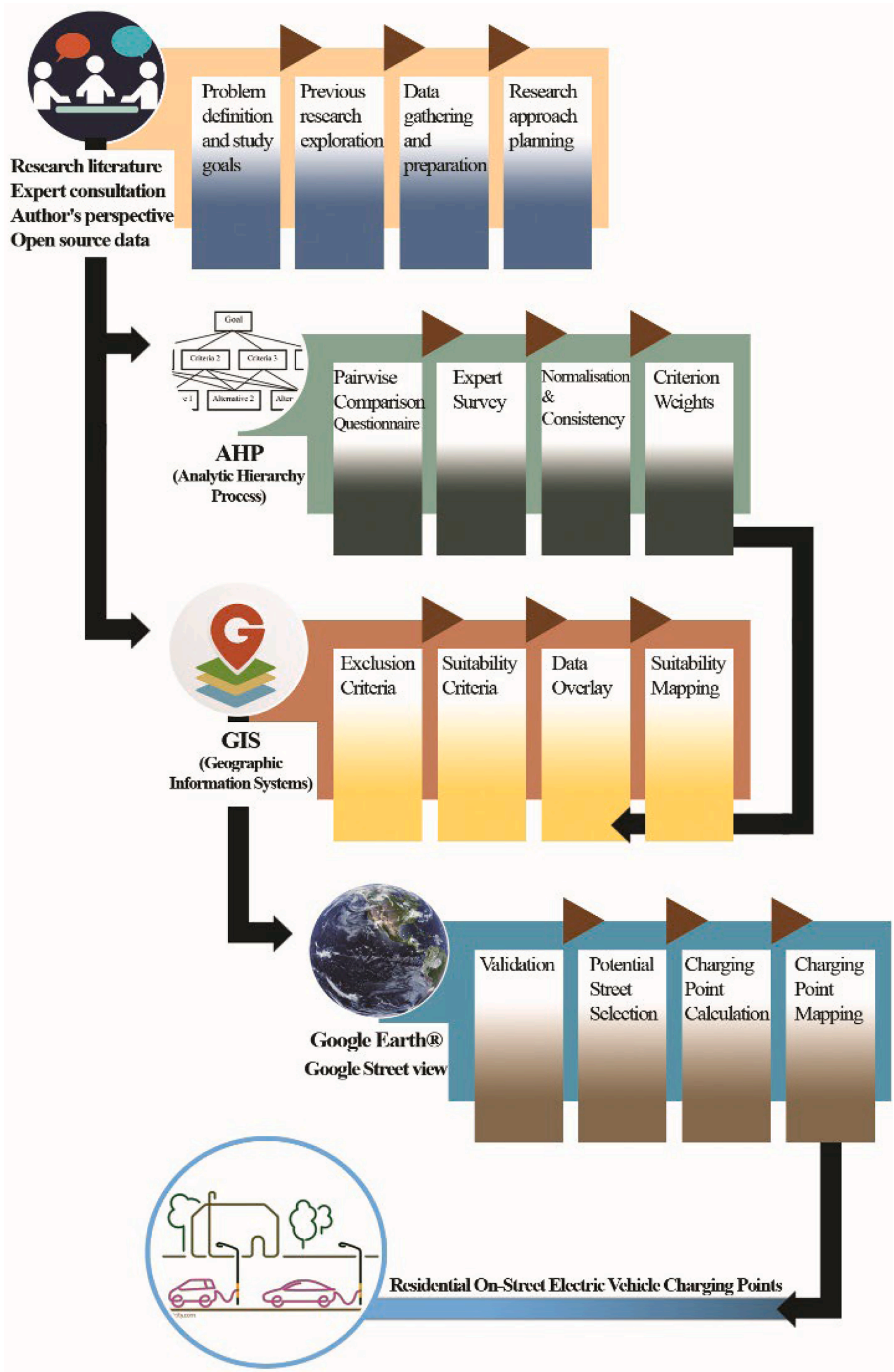

Fig. 2. Study Road Map.

Table 2
Summary of GIS criteria, data types, sources, and processes.

Criteria		GIS Specific Processes	Type of Data	Data Source
Suitability Criteria				
SC1.1	Residential Proximity	Query - Multiple Ring Buffer - Dissolve - Union	polygon shape file	OSM exports for Birmingham by BBBike.org
SC1.2	Distance to Available EVCPs	Query - Multiple Ring Buffer - Dissolve - Union	Point shape file	OSM exports for Birmingham by BBBike.org
SC2.1	Population Density	Join - Query - Count - Dissolve	Text-extracted data joined with Birmingham ward shapefile	2021 Census profile for wards in Birmingham Overview | Population and census | Birmingham City Council Wards (May 2023) Boundaries UK BFC | Wards (May 2023) Boundaries UK BFC | Open Geography Portal (statistics.gov.uk)
SC2.2	Inclusive EVCPs Distribution for Disabilities	Join - Query - Count - Dissolve	Text-extracted data joined with Birmingham ward shapefile	2021 Census profile for wards in Birmingham Overview | Population and census | Birmingham City Council Wards (May 2023) Boundaries UK BFC | Wards (May 2023) Boundaries UK BFC | Open Geography Portal (statistics.gov.uk)
SC2.3	EV-Prone Age Groups	Join - Query - Count - Dissolve	Text-extracted data joined with Birmingham ward shapefile	2021 Census profile for wards in Birmingham Overview | Population and census | Birmingham City Council Wards (May 2023) Boundaries UK BFC | Wards (May 2023) Boundaries UK BFC | Open Geography Portal (statistics.gov.uk)
SC3.1	Air Quality Level	Project - IDW - Reclassify - Raster to Polygon - Dissolve	Text-extracted data converted to a point shapefile.	2022 Air Quality (ASR) https://www.birmingham.gov.uk/info/20076/pollution/1276/air_pollution
SC3.2	Noise Pollution	Clip - Query - Dissolve - Union	polygon shape file	Defra Spatial Data Download https://environment.data.gov.uk/DefraDataDownload
SC3.3	Road Slope Compatibility (≤10 %)	Mosaic - Clip - Slope -Reclassify - Raster to Polygon -Dissolve	Raster (Pixel Depth: 32 Bit)	EarthExplorer (usgs.gov)
Exclusion Criteria				
ExC1	Road Speed	Query - Erase	Line shape file	BBBike extracts OpenStreetMap (OSM, Garmin, Shapefile etc.)
ExC2	Road Type	Query - Erase	Line shape file	BBBike extracts OpenStreetMap (OSM, Garmin, Shapefile etc.)
ExC3	Potential Public Services Locations for Non-Residential On-Street Charging	Query - Buffer - Clip	polygon shape file	OSM exports for Birmingham by BBBike.org
ExC4	Road Slope (>10 %)	Mosaic - Clip - Slope -Reclassify - Raster to Polygon -Dissolve	Raster (Pixel Depth: 32 Bit)	EarthExplorer (usgs.gov)

evaluate and rank multifaceted factors influencing complex decisions. According to the Table 3, the process involves assessing factor pairs on a defined 9-point scale based on expert judgments, with 1 representing equal importance and 9 indicating extreme importance. AHP's rigorous methodology and reliance on expert opinions make it a valuable tool for decision-making in GIS contexts.

The structured hierarchical framework created in three primary levels: the overarching objective, criteria, and sub-criteria (Fig. 3). At each level of this hierarchy, factors are meticulously paired and compared, leading to the development of four matrices. These matrices serve as pairwise comparison matrices, essential tools for quantifying relative preferences or importance among elements or criteria. Experts assign values, typically on a scale of 1 to 9, to express how one element relates to another within these matrices (Saaty, 1977).

The questionnaire employed in our hierarchical analysis and multi-criteria decision-making is referred to as an expert questionnaire. This questionnaire involves pairwise comparisons of options and employs Mr. Saati's nine-grade scale for scoring, as outlined in the provided table. The questionnaire was distributed to 20 experts from diverse professional backgrounds via email and consist of standardized questions and content for uniformity. It included introductory greetings, a participant consent form, inquiries about participants' personal and professional characteristics, explanations regarding the study's purpose, a concise introduction to criteria and sub-criteria, instructions for questionnaire completion, and the crucial pairwise comparisons to be conducted by participants. As depicted in Fig. 4, the largest segment (39.13 %) specialized in the domain of Transportation and Mobility, followed closely by those in Civil Engineering (30.43 %), and Academic Researcher roles in related fields (26.09 %). This diverse array of

Table 3
Saaty's 1–9 scale of pairwise comparisons.

Intensity of Importance	Definition
1	Equally Important Preferred
2	Equally to Moderately Important Preferred
3	Moderately Important Preferred
4	Moderately to Strongly Important Preferred
5	Strongly Important Preferred
6	Strongly to Very Strongly Important Preferred
7	Very Strongly Important Preferred
8	Very Strongly to Extremely Important Preferred
9	Extremely Important Preferred

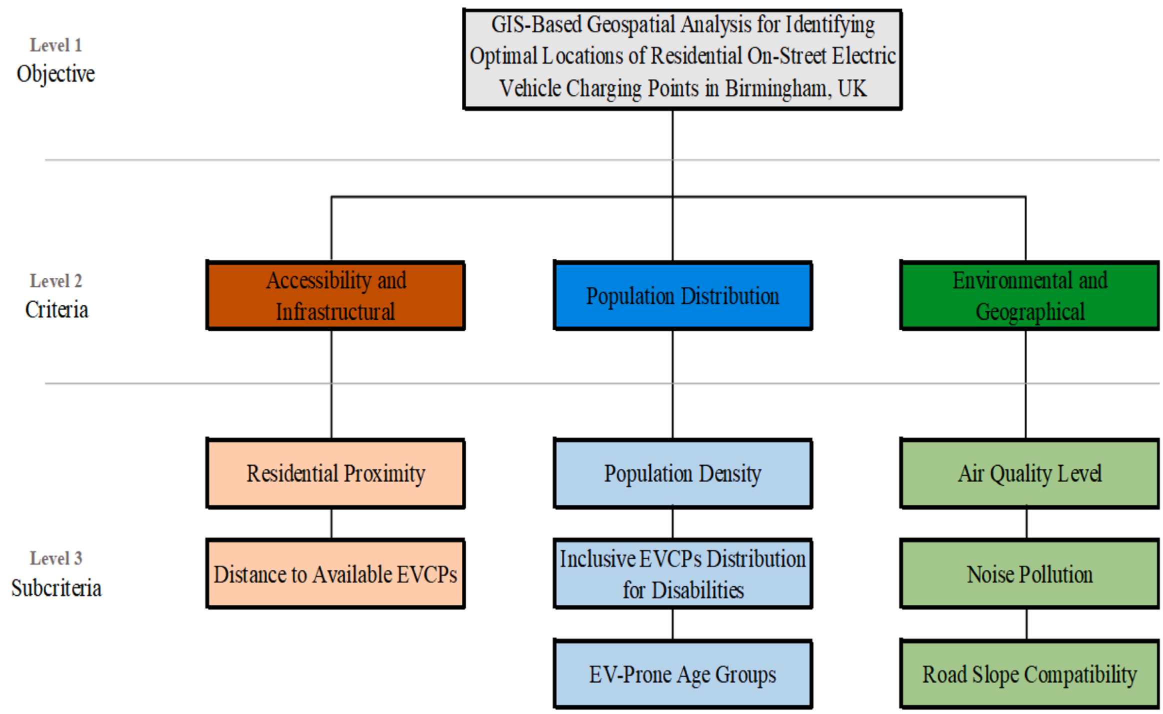

Fig. 3. Hierarchical structure of AHP model.

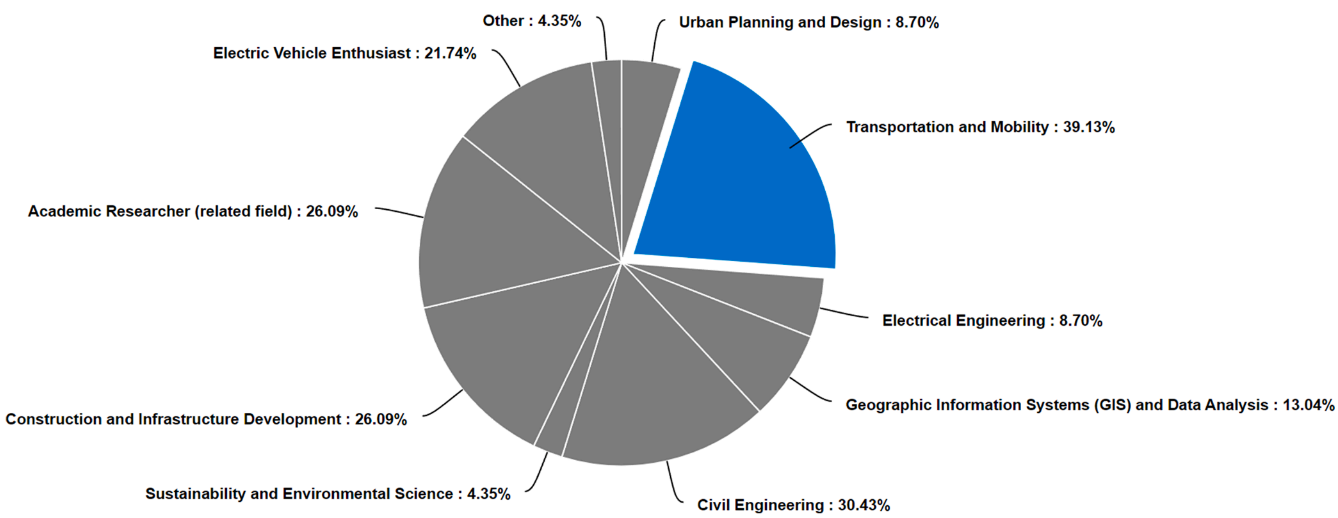

Fig. 4. Expertise distribution among study participants.

expertise significantly enriched the analytical approach undertaken in this study.

In terms of their professional tenure, a substantial majority (65.22 %) possessed more than a decade of experience within their respective domains, highlighting the wealth of seasoned knowledge among the participants. Furthermore, 21.74 % had 6–10 years of experience, while 13.05 % had <5 years of professional involvement, collectively representing a panel of highly accomplished individuals (see Fig. 5). This diverse and accomplished group of experts played a pivotal role in shaping the study's methodological foundation, contributing invaluable insights and experiences.

The Analytical Hierarchy Process (AHP) Excel Template for MS Excel 2013 by Klaus D. Goepel was utilized for this study (Goepel, 2013). In the AHP analysis, we utilized 8 distinct criteria (Residential Proximity, Distance to Available EVCPs, Population Density, Inclusive EVCPs Distribution for Disabilities, EV-Prone Age Groups, Air Quality Level, Noise Pollution, and Road Slope Compatibility) to identify the most suitable sites for EV charging stations in the region. Subsequently, experts shared their perspectives by completing a questionnaire. Once input from each expert was collected, the responses underwent scrutiny for consistency. Consistency assessment, crucial to the AHP methodology, employs the Consistency Ratio (CR), computed as the ratio of Consistency Index (CI) to Random Index (RI) using the Alonson and Lamata linear fit method (2006). In this study, the CR calculation process involved computing compatibility ratios for individual and collective expert judgments. The equations employed for these calculations are provided below, where Eq. (1) corresponds to the Consistency Index (CI), Eq. (2) represents the Compatibility Ratio (CR), and Eq. (3) relates to the Random Index (RI). In these mathematical expressions, "N" signifies the total number of elements or factors taken into account in the comparison matrices.

$$CI = \lambda max - NN - 1 \tag{1}$$

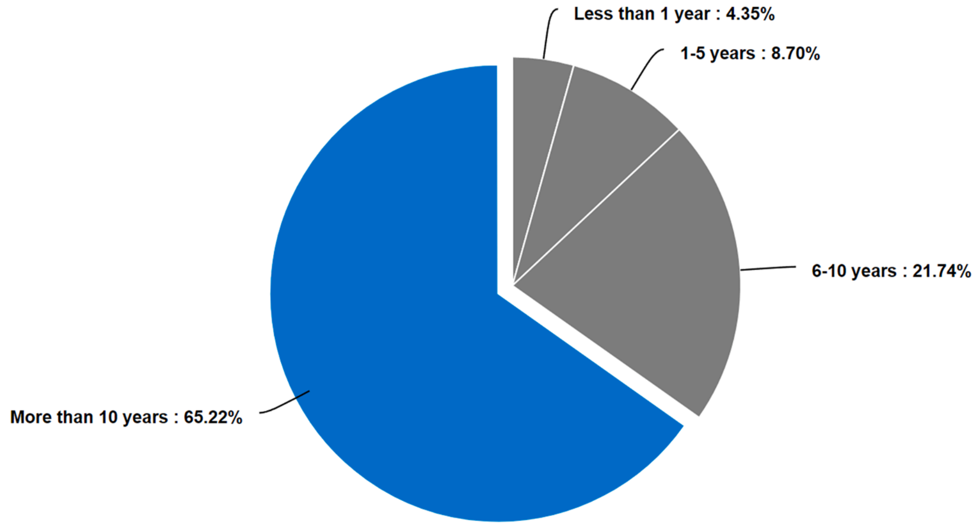

Fig. 5. Professional experience distribution among study participants.

$$CR = CIRI \tag{2}$$

$$RI = \lambda max - N2.7699N - 4.3513 - N \tag{3}$$

The principle eigenvalue λ_{max} was derived either through the priority eigenvector from RGMM for individual judgments or the EVM for aggregated judgments. Subsequently, the CR consistency ratio was determined using the Alonso/Lamata linear fit method (Alonso & Lamata, 2006). A CR value at or below 0.1 signifies matrix consistency, while higher ratios necessitate matrix reconstruction (Saaty, 1987). It's crucial to note that CR is the key parameter for validating AHP results, ensuring the outcomes are balanced and coherent.

4.8. Utilising geographic information systems (GIS) for geospatial analysis of EV charging point locations

This data is sourced from diverse databases, encompassing geographic, demographic, environmental, and infrastructure-related datasets. The systematic data collection step holds great importance within GIS analysis, as it furnishes the essential information for assessing potential EV charging point sites in Birmingham, UK. Table 2 provides a concise overview of the criteria, data types, sources, and specific GIS processes used in this study. The "Type of Data" column clarifies the format of data for each criterion, aiding in understanding its nature. The "Data Source" column references the data origins, ensuring transparency and analysis credibility. Furthermore, the "Specific GIS Processes" column outlines the GIS methods linked to each criterion, explaining the data processing and analysis techniques employed.

In the data acquisition process, multiple datasets were employed, encompassing crucial demographic information sourced from the ONS Geography website (Open Geography Portal) at the ward level. Population density metrics (individuals per square kilometer) for each ward were meticulously extracted from the respective tables. For the Inclusive EVCPs Distribution for Disabilities criterion, where density unit information was unavailable, we extracted the count of individuals falling under the category of one or more disabilities as per the Equality Act in households (LLTI in 2011) from ward-specific tables. These figures were then divided by the area of the respective regions to calculate the density of the disabled population. In the context of the EV-Prone Age Groups factor, which focused on age groups ranging from 18 to 34 years within each ward, we computed the count of individuals falling within this age bracket and expressed it as a percentage relative to the total ward population. All demographic data was meticulously stored in EXCEL file format with a CSV extension (MS-DOS) to ensure seamless compatibility with GIS software. Additionally, a segment of the data was obtained in vector format using BBBike. BBBike is a service that extracts data from OpenStreetMap (OSM), a publicly available database renowned for its capability to precisely gather specific geographic areas in various data formats. This method enhanced the flexibility of retrieving geographic data and expanded its utility by granting access to OpenStreetMap (OSM) shape files and raw data resources.

The vector data, obtained in the form of a shapefile, contained crucial geospatial information within the study area, including precise locations of charging points and data on various building types in polygon and point formats, essential for evaluating the Residential Proximity factor. Road data was also systematically extracted, allowing for the identification of road types and their respective maximum allowable speeds. Additionally, information concerning the location of existing parking lots was acquired in polygon format, contributing to the assessment of potential public service locations for the non-residential on-street charging factor. The Air Quality Level factor draws on the 2022 Air Quality Annual Status Report (ASR), which covers 129 monitoring stations and provides key metrics, such as the Annual Mean NO_2 Monitoring Results from both Automatic and Non-Automatic Monitoring ($\mu g/m^3$) for 2021. For noise pollution, data was sourced from the ArcGIS web application, detailing road noise levels in the UK in Lden units, which account for 24-hour annual average noise levels with distinct weighting for evening and nighttime periods. Noise data was modeled on a 10-meter grid at a receiver height of 4 meters above the ground, with polygons generated by merging neighboring grid cells that cover a range of noise levels from +75.0 dB to below +54.9 dB Defra Data Services Platform (online).

Fig. 6 serves as a visual summary, highlighting specific data layers employed in the GIS analysis. These layers comprise demographic data, location specifics, and geographical and environmental information. The figure visually illustrates a subset of the datasets applied in the assessment of suitability criteria for electric vehicle charging points (EVCPs) in Birmingham, UK.

4.9. Criteria classification

To ensure measurement accuracy and consistency, a ranking system was applied to classify and standardize the geographic data for each measurement. This system, derived from an examination of research literature and study area requirements, is elaborated in Section 3.2. It employs a scale ranging from 1 to 3, each associated with a distinct color code signifying the suitability of the data point. A rating of 1 designates "optimal suitability" and is represented by the color green. A rating of 2

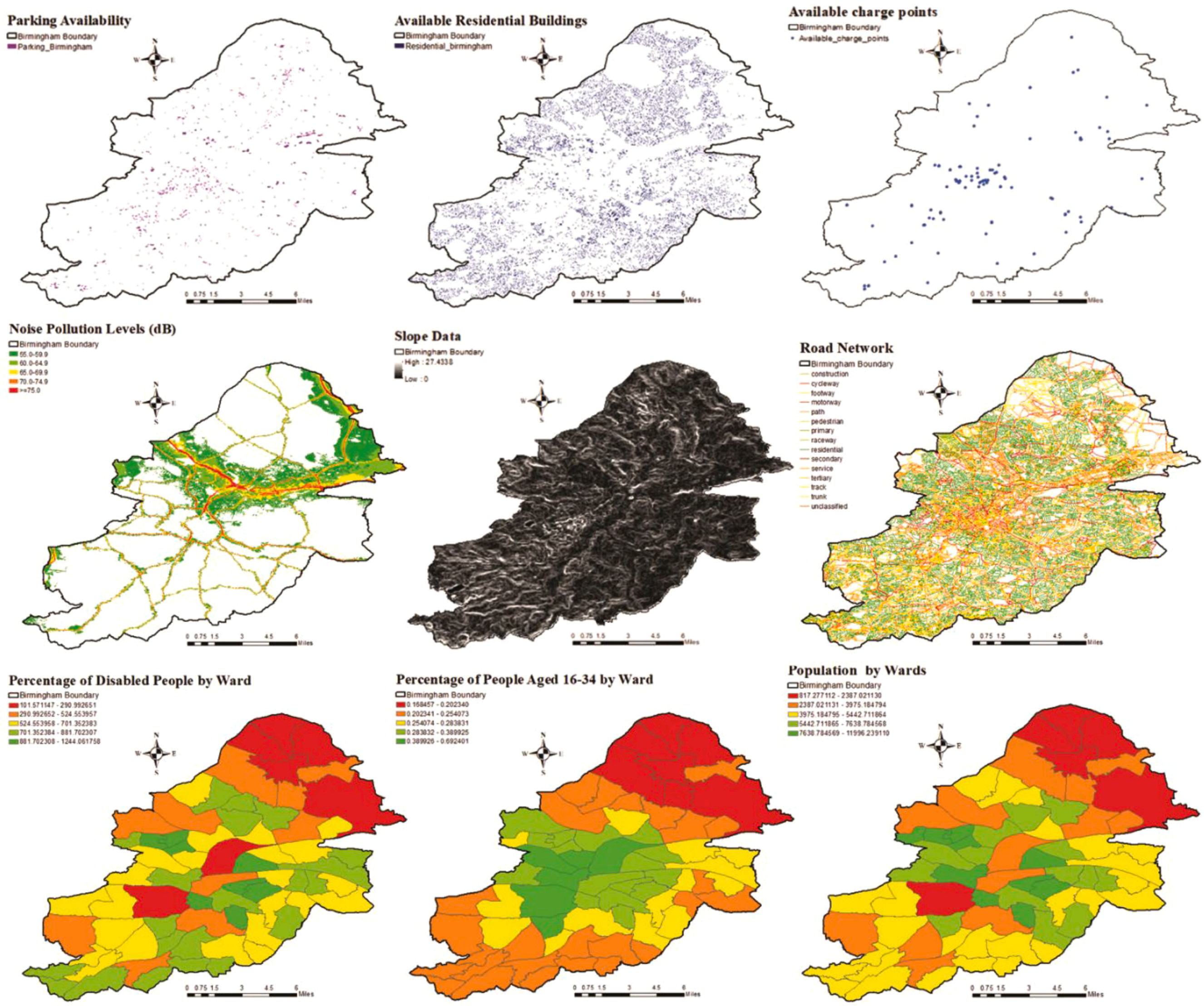

Fig. 6. Input data layers in GIS.

corresponds to "moderate suitability" denoted by yellow, while a rating of 3 indicates "limited suitability" depicted in orange. This system enables a visual representation of diverse suitability levels within geographic data, facilitating the identification of areas with distinct compatibility or suitability for specific objectives or criteria, as presented in Table 4.

5. . Result & finding

5.1. Analysis of analytic hierarchy process (AHP)

Recognizing the inherent variability in human judgment, Gudiyangada Nachappa et al. (2020) this study collected responses from 20 experts, with five responses being incomplete. Consistency rates (CR) were calculated for 15 judgments, leading to the exclusion of three inconsistent responses. Consequently, the analysis considered the opinions of 12 experts. Impressively, the CR consistency ratio for the 15 completed judgments revealed that 12 experts achieved a CR equal to or below 10 %, aligning with Saati's criteria (Saaty, 1987) for valid results. Consequently, 12 judgments were categorised as consistent, while three were deemed inconsistent and subsequently excluded from the analytical process. Incorporating input from 12 experts and employing pairwise comparison matrices, the weight of each suitability criterion was determined, subsequently serving as the weight for each criterion layer in the GIS program. The weights of the criteria and sub-criteria determined through the AHP method are presented in Table 5 and Fig. 7.

After evaluating and calculating the total weights for each of the 8 sub criteria, as recorded in Table 5, Fig. 8 visually illustrates the relative ranking of these sub-criteria. In this ranking, the sub criteria are arranged in descending order, with the most influential or heavily weighted sub criterion placed at the top. This figure provides a quick and clear reference for understanding the importance of each sub-criterion in the decision-making process, aiding in the prioritization of factors under consideration.

Among the sub-criteria, "Distance to available EV charging points" (0.2987) emerges as the most heavily weighted factor, underscoring the priority for new EVCPs to be situated at a considerable distance from existing charging infrastructure. This underscores the imperative of expanding the charging network strategically, while concurrently ensuring an integrated dispersion of facilities, equitable accessibility, and fair design principles. The sub-criterion Residential proximity (0.1938) occupies a notable position in the second level of importance, emphasizing the importance of placing EVCPs in close proximity to residential areas. This alignment underscores the consistency of this factor with the study's goals, which center around positioning within residential zones, and the practical necessity for accessibility. It places a

Table 4
Siting suitability criteria, classification, and ratings.

Main Criteria		Sub-Criteria	Class	Suitability	Rating
C1 Accessibility and Infrastructural	SC1.1	Residential Proximity	≤160 m	Optimal	1
			160–400 m	Moderate	2
			400–800 m	Limited	3
	SC1.2	Distance to Available EVCPs	>800 m	Optimal	1
			400–800 m	Moderate	2
			<400 m	Limited	3
C2 Population Distribution	SC2.1	Population Density	7041 - 11,996	Optimal	1
			3778 - 7040	Moderate	2
			817 - 3778	Limited	3
	SC2.2	Inclusive EVCPs Distribution for Disabilities	748–1244	Optimal	1
			396–748	Moderate	2
			102–396	Limited	3
	SC2.3	EV-Prone Age Groups	34 %–100 %	Optimal	1
			24 %–34 %	Moderate	2
			17 %–24 %	Limited	3
C3 Environmental and Geographical	SC3.1	Air Quality Level	>36 μg/m3	Optimal	1
			30–36 μg/m3	Moderate	2
			<30 μg/m3	Limited	3
	SC3.2	Noise Pollution	≥70 dB	Optimal	1
			60–70 dB	Moderate	2
			<60 dB	Limited	3
	SC3.3	Road Slope Compatibility	<5 %	Optimal	1
			5 %–8 %	Moderate	2
			8 %–10 %	Limited	3

Table 5
AHP weighting of criteria and subcriteria.

	Criteria (C)	Criteria weight Cwi	Rank Cwi		Subcriteria (SC)	Subcriteria Weight SCwi	Rank Scwi	Total Weight (Twi) Twi = Cwi × SCwi	Rank Twi
C1	Accessibility and Infrastructural	0.4925	1	SC1.1	Residential Proximity	0.3935	2	0.1938	2
				SC1.2	Distance to Available EVSc	0.6065	1	0.2987	1
					Total	1		0.4925	
C2	Population Distribution	0.2082	3	SC2.1	Population Density	0.4039	1	0.0841	4
				SC2.2	Inclusive EVCPs Distribution for Disabilities	0.3312	2	0.0690	6
				SC2.3	EV-Prone Age Groups	0.2649	3	0.0552	8
					Total	1		0.2082	
C3	Environmental and Geographical	0.2993	2	SC3.1	Air Quality Level	0.5434	1	0.1626	3
				SC3.2	Noise Pollution	0.2598	2	0.0778	5
				SC3.3	Road Slope Compatibility	0.1968	3	0.0589	7
					Total	1		0.2993	

premium on the convenience and reduction of walking distances for residents. Air quality level (0.1626) also carries considerable importance, underscoring the significance of environmental factors in making decisions regarding the placement of EVCPs. This necessitates a focus on regions with potential air quality concerns, where the adoption of electric vehicles can yield positive environmental benefits. Noise pollution and the Inclusive EVCPs Distribution for Disabilities are relatively new criteria introduced in the evaluation process. However, they have demonstrated their significance by maintaining their weight alongside established factors. Remarkably, they hold a higher level of importance compared to criteria such as age groups and road slope, which have been utilised in previous studies. However, as per the authors' perspective, to enhance convenience and improve accessibility, there is a need for increased provisions catering to individuals with disabilities, and greater emphasis should be placed on inclusive design considerations for this demographic.

5.2. Analysis of geographic information systems (GIS)

5.2.1. Spatial exclusion criteria analysis

Road Speed: As previously stated, this study's initial GIS processing step entails the exclusion of streets and locations outside the study's scope. In accordance with regulations outlined in The Highway Code, Road Safety and Vehicle Rules - (GOV.UK), the established maximum speed limit within built-up areas is 30 miles per hour, equivalent to 48 km per hour. Furthermore, Rule 249 of the Highway Code (The Highway Code - Waiting and parking (238 to 252) - Guidance - GOV.UK) that any vehicle parked overnight on streets with speeds exceeding 30 miles per hour must have its parking lights activated. Given these regulatory provisions and safety considerations, the practice of overnight parking on streets with speeds exceeding 30 miles per hour is deemed unviable and unsafe, especially within the context of this study's focus on residential areas. Consequently, such streets have been excluded from the analysis (see Fig. 9). Road Type: In the subsequent phase, the elimination process is conducted based on road type, given that this investigation focuses on the placement of on-street EVCPs within residential areas. Hence, the deployment of these charging points in non-residential streets, which frequently serve different purposes, is regarded as unfeasible, and they are therefore excluded from further deliberation within the study's scope (see Fig. 9).

The study area spans 267.816 square kilometers and includes 51,216 road segments, covering various road types, including highways, minor

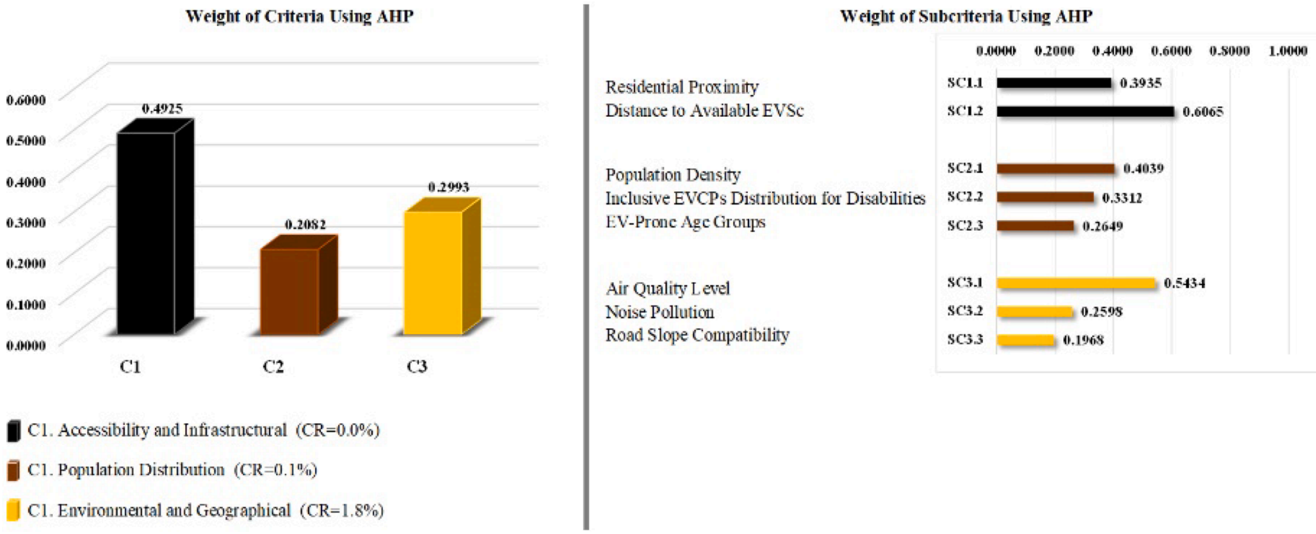

Fig. 7. Weighting of criteria and subcriteria using AHP.

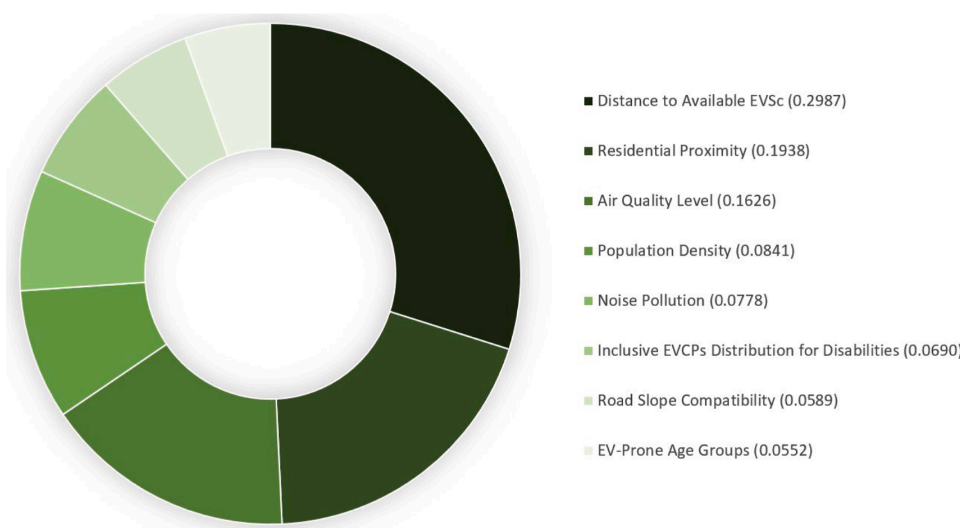

Fig. 8. Total weight of subcriteria.

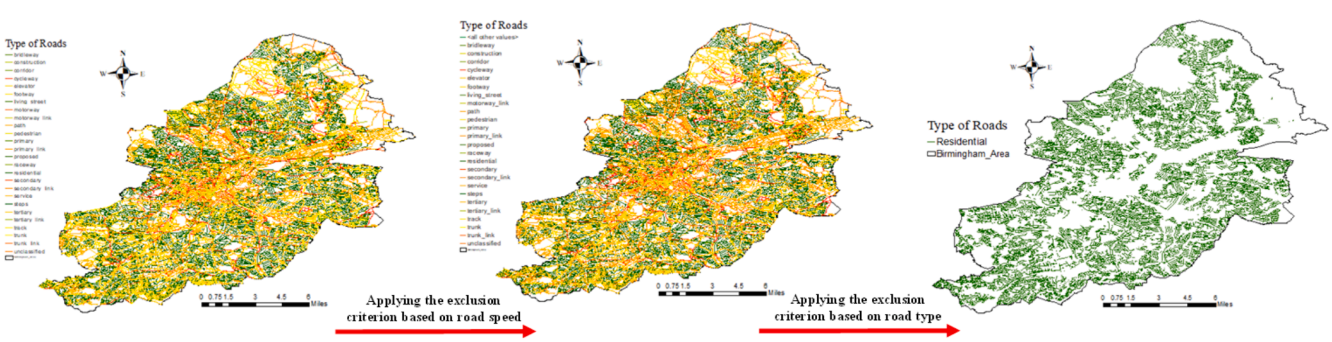

Fig. 9. Excluding road types and speed criteria in Birmingham area.

roads, residential streets, as well as bicycle paths, and dedicated sidewalks. Following the implementation of speed and road type restrictions, approximately 74 % of the road sections were eliminated, leaving only 13,025 road segments for further analysis. Areas identified as potential public service locations for non-residential on-street charging, characterized by adequate space for long-term car parking and meeting the required standards for charging point installation, particularly for destination charging (i.e., capable of accommodating a minimum of 25 cars or more, as per (Chen, Kockelman & Khan, 2013)), were intentionally excluded from the study's purview. To implement this criterion, the study utilised a polygon file format map of parking spaces in Birmingham. Specifically, parking spaces with sufficient area to

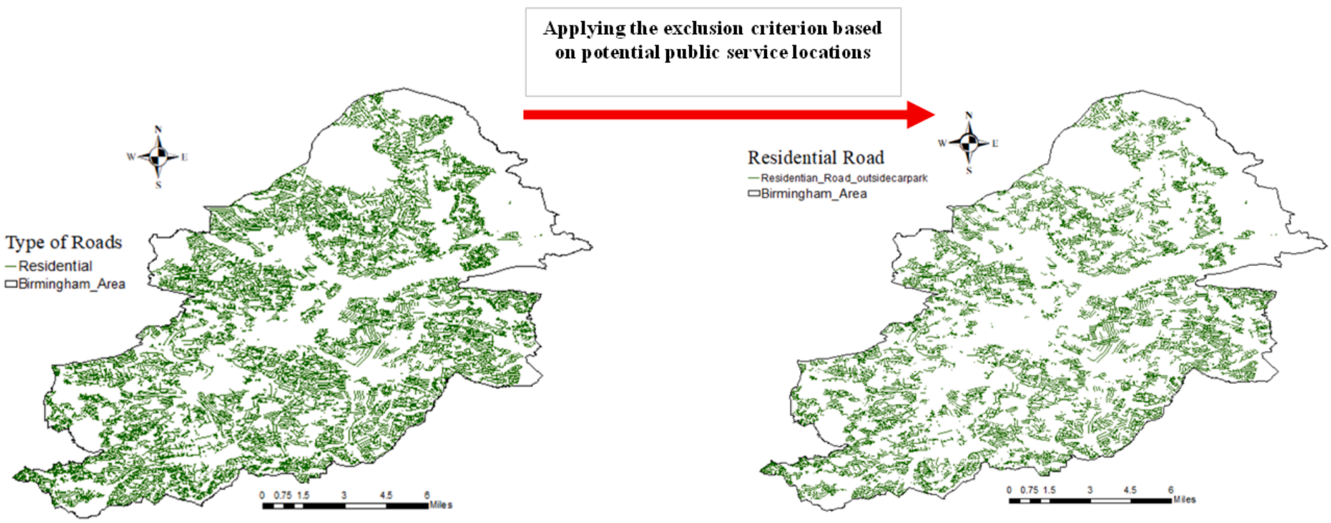

Fig. 10. Road segments after exclusion of potential charging service locations.

accommodate a minimum of 25 cars were selected, resulting in the inclusion of 1276 parking spaces out of a total of 1754. Subsequently, an optimal walking distance threshold of 2 min was applied, leading to the exclusion of all streets within a 160-meter radius from the study area's boundaries. After implementing this criterion, a total of 10,415 road segments, covering a length of 1299 km, were retained for further analysis (see Fig. 10).

To eliminate roads with slopes exceeding 10 % due to safety, efficiency, and accessibility concerns, several steps were taken. Initially, a slope map was obtained from the USGS website and imported into the GIS environment, including clipping to the specific study area, reclassification to distinguish slope ranges (0–5 %, 5–8 %, 8–10 %, and above 10 %), and conversion from raster to polygon format. This transformation allowed for the identification of areas with slopes exceeding 10 % (Observe the red regions depicted on the right-side map within Fig. 11). Ultimately, these high-slope areas were excluded from the study area, ensuring that only road segments with safer and more accessible slopes were considered for further analysis. The remaining road segments have a combined length of 1289.46 km.

After applying all four exclusion criteria, which included "road type," "road speed," "potential public service locations for non-residential on-street charging," and "Road Slope (>10 %)," approximately 28.55 % (76.485 km2) of the total study area and 75.35 % (3942.033 km) of all the roads within the study area were removed based on the exclusion criteria.

5.2.2. *Spatial suitability criteria analysis*

To achieve the best RO-EVCP placements, suitability criteria are employed alongside exclusion criteria. This process involves classifying the 8 suitability criteria within the study area, aligning with the specifications outlined in Table 4. Different thresholds are utilised to create a normalisation process aimed at integrating the criteria based on their values. The resulting normalisation maps, provided in Fig. 12, indicate optimal suitable locations in green (class 1), moderately suitable areas in yellow (class 2), and locations with limited suitability in orange (class 3). The execution of the "Residential Proximity" suitability criterion in this study involved the utilisation of a geospatial layer containing comprehensive information on all registered residential buildings within the Birmingham area. This dataset encompassed a substantial number of residential structures, totaling 189,494 individual houses, which collectively covered an expansive area measuring 1,8017,313 m^2s. The average area of these residential units was found to be about 95 m^2s per dwelling. While many express a willingness to walk 2–5 minutes to

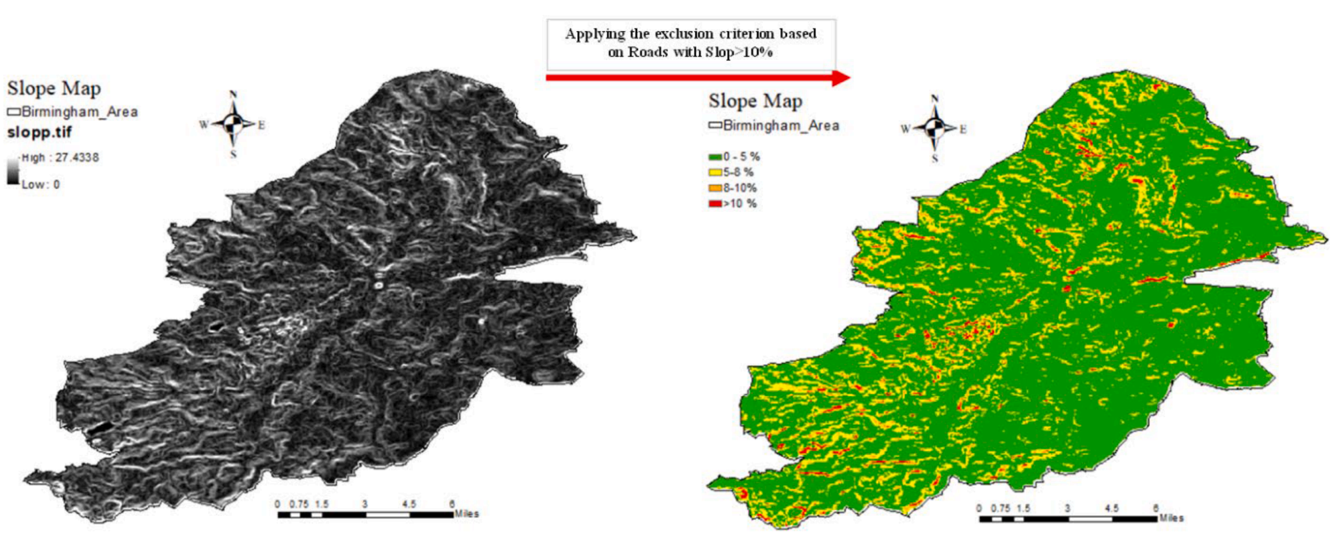

Fig. 11. Excluding roads with slopes exceeding 10 % from the study area.

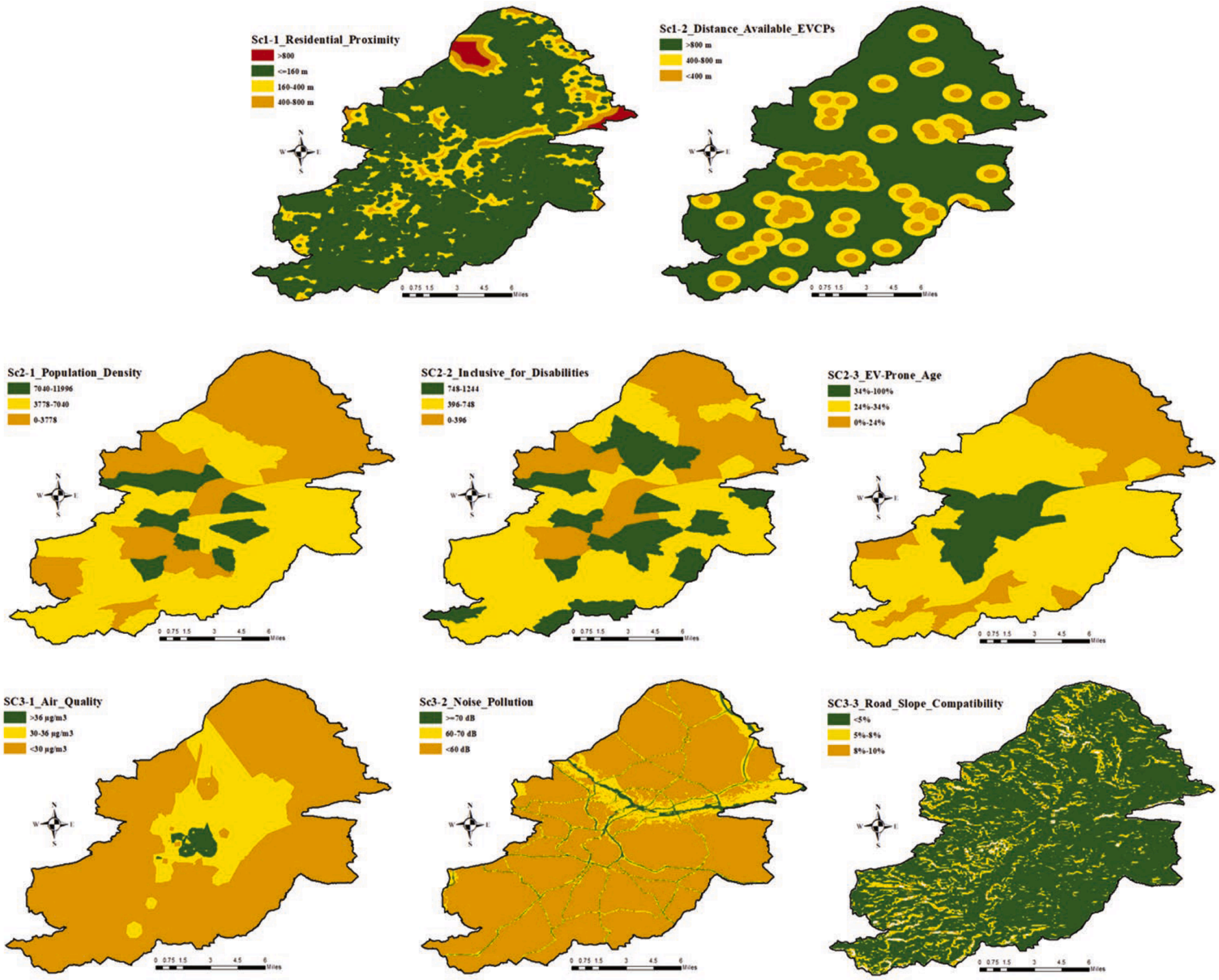

Fig. 12. Classified criteria layers in GIS.

access charging facilities (Field Dynamics, 2021), most currently walk less than 2 minutes to reach their vehicles (Department for Transport, 2021), highlighting a gap between preferences and behavior. This study focuses on optimizing on-street charging accessibility, particularly for demographics like parents, individuals with disabilities, and women, by considering a walking distance of 2–5 minutes as suggested by research.

In the pursuit of determining the optimal distances that residents should ideally cover on foot to access electric vehicle charging points (EVCPs) from their respective residential abodes, a geospatial analysis technique known as the "buffer" command was meticulously employed. This analytical approach took into consideration the Euclidean distance metric, which calculates distances in a straight-line fashion. Consequently, the computed walking distances were systematically categorised into three distinct classes or ranges, namely: 0–160 m, 160–400 m, and distances exceeding 400 m. The graphical representation of these categories is visually depicted in Fig. 12, offering a clear visualization of the suitability zones for EVCP placement concerning residential areas. Similarly, for the "Distance to Available EVCPs" suitability criterion, a parallel process was undertaken, making use of the buffer command. This operation was conducted on a point layer that contained geographical data related to the current electric vehicle charging points (EVCPs) within the study area. Specifically, the objective was to establish boundaries at two specific distance thresholds: 400 m and 800 m, from these pre-existing charging stations Fig. 12.

The aim of this spatial analysis was to define regions that represent varying levels of proximity to the existing charging infrastructure. Areas situated beyond the 800-meter boundary were deemed highly favorable, indicating a greater distance from the available charging points. Incorporating demographic suitability criteria, such as Population Density, Inclusive EVCPs Distribution for Disabilities, EV-Prone Age Groups into the GIS analysis involved a multi-step procedure. Initially, statistical data from (Kaur, 2021) was collected and adjusted to align with the specific criteria detailed in Section 3.4. This demographic information, presented in text format, was then imported into the GIS program for spatial analysis. Given the initial division of this data by ward, a join operation was performed to link it with a ward-based layer. The natural breaks classification method was employed to categorise demographic attributes, with the aim of achieving meaningful and balanced statistical populations. After careful analysis and refinement, the categories in Table 4 were established and further reclassified into three distinct classes (1, 2, and 3) Fig. 12.

The "Air Quality Level" data, sourced from the 2022 Air Quality Annual Status Report (ASR) by the Birmingham City Council, was initially provided in text format. To make this data usable for spatial analysis within a Geographic Information System (GIS), several steps were taken. First, interpolation, specifically Inverse Distance Weighting (IDW), was employed to create a raster layer that represented air quality levels across the study area. This interpolation process helped generate a continuous surface of air quality measurements. Subsequently, this raster layer underwent reclassification, a process where continuous data is grouped into discrete classes or categories. Once reclassified, the raster layer was converted into a vector layer, making it compatible with GIS analysis. Finally, the data was categorised into three distinct classes, as illustrated in Fig. 12. To incorporate the "Noise Pollution" suitability criterion into the analysis, data representing noise levels in terms of Lden (day-evening-night noise levels) was introduced into the GIS as a vector file. Subsequently, this data was subjected to reclassification based on predefined noise classes that aligned with the study's classification criteria, as outlined in Table 4. Finally, a normalisation process was applied, categorising the noise levels into three classes, denoted as 1, 2, and 3 (see Fig. 12). This standardization facilitated the alignment of the noise pollution criterion with other spatial layers in the analysis, ensuring its seamless integration into the overall evaluation process. In this phase of the analysis, the slope layer, which was generated during the exclusion criteria stage and depicted slope percentages, was utilised. To integrate this layer into the overall evaluation, it was subjected to normalisation based on predefined slope classifications (see Table 4). Areas with a slope of up to 5 % were categorised as Class 1, those falling between 5 % and 8 % were assigned Class 2, and regions with a slope ranging from 8 % to 10 % were designated as Class 3 (see Fig. 12).

5.2.3. Spatial suitability map

A spatial suitability map is a visual tool utilised in geographic information systems (GIS) and spatial analysis to illustrate regions suitable for specific purposes, such as the placement of on-street electric vehicle charging points (RO-EVCPs). This map aids decision-makers and stakeholders in identifying suitable locations for RO-EVCP installation, facilitating informed urban planning and infrastructure development decisions. In this study, we have designed a spatial suitability map to depict the appropriateness of various geographical locations for RO-EVCP placement. To create this map, we conducted proportion mapping by linearly integrating weighted geographical sub-models, with the weights of each model determined through the Analytic Hierarchy Process (AHP), as detailed in Section 5.1. The suitability map encompasses multiple criteria layers, including Residential Proximity, Distance to Available EVCPs, Population Density, Inclusive EVCPs Distribution for Disabilities, EV-Prone Age Groups, Air Quality Level, Noise Pollution, and Road Slope Compatibility. These criteria were employed to categorise areas into distinct classes, visually represented by color-coding and numerical indicators. "Optimal" areas are depicted in green, "moderate" areas in yellow, and "limited" areas in orange.

In conclusion, this research led to the development of an Electric Vehicle Charge Points Suitability Index (EVCP-SI) model, as expressed by the following equation:

$$EVCP-SI = (RP_R \times RP_W) + (CD_R \times CD_W) + (PD_R \times PD_W) + (DD_R \times DD_W) + (AG_R \times AG_W) + (AQ_R \times AQ_W) + (NP_R \times NP_W) + (RS_R \times RS_W) \quad (7)$$

In this equation, EVCP-SI represents the Electric Vehicle Charge Points Suitability Index, while: RP_R: Residential Proximity classification rate, RP_W: Residential Proximity AHP weight, CD_R: Distance to Available EVCPs classification rate, CD_W: Distance to Available EVCPs AHP weight, PD_R: Population Density classification rate,PD_W: Population Density AHP weight, DD_R: Inclusive EVCPs Distribution for Disabilities classification rate, DD_W: Inclusive EVCPs Distribution for Disabilities AHP weight, AG_R: EV-Prone Age Groups classification rate,AG_W: EV-Prone Age Groups AHP weight,AQ_R: Air Quality Level classification rate,AQ_W: Air Quality Level AHP weight, NP_R: Noise Pollution classification rate, NP_W: Noise Pollution AHP weight, RS_R: Road Slope Compatibility classification rate, RS_W: Road Slope Compatibility AHP weight.

In GIS, the overlay command was used to merge the sub-criterion layers. These eight pre-classified layers were consolidated into a single layer. In this newly created layer, Eq. (8) was applied to a newly added column in the attribute table using the Field Calculator menu.

$$EVCP-SI = (RP_R \times 0.1938) + (CD_R \times 0.2987) + (PD_R \times 0.0841) + (DD_R \times 0.0690) + (AG_R \times 0.0552) + (AQ_R \times 0.1626) + (NP_R \times 0.0778) + (RS_R \times 0.0589) \quad (8)$$

The result of this weighted overlap analysis was the generation of a suitability map for Electric Vehicle Charge Points (EVCPs), as depicted in Fig. 13.

Creating the suitability map was a meticulous and comprehensive procedure that demanded in-depth analysis. It involved the careful consideration of various factors, including of accessibility and infrastructure, demographic characteristics, and environmental and geographical impact. This rigorous assessment was conducted to guarantee that the chosen sites closely adhered to the predefined suitability criteria. The green areas depicted on the suitability map signify locations that are optimal suitable for the installation of charging stations. These regions make up a section of the study area, constituting 17.830 square kilometers within the total study area of 267.767 square kilometers. As mentioned, these specific locations have been identified based on stringent criteria, rendering them as top-priority choices for the placement of electric vehicle charging points. Furthermore, it's important to highlight that the yellow areas, denoting moderate suitability and covering 105.786 square kilometers, are categorised as regions with a medium priority level, whereas the orange areas, spanning an area of 144.150 square kilometers and indicating limited suitability, are classified as having a lower priority for the installation of charging points. These distinctions play a pivotal role in the development of a prioritization framework, ensuring that locations are evaluated and assigned priority levels based on their suitability.

It is important to emphasize that to precisely identify and present the ultimate list of residential street locations and the corresponding number of charging points, the integration of this suitability map with the map of suitable residential streets chosen in preceding sections of this study is imperative. Additionally, the incorporation of new factors for the selection of locations and the determination of optimal quantities will be essential. This comprehensive process will be elucidated in the subsequent section, providing a detailed insight into the final decision-making framework for the installation of electric vehicle charging infrastructure.

5.3. Identification of optimal charging point locations and visual validation

In this study, focusing on the selection of optimal Residential On-Street Electric Vehicle Charging Points in Birmingham, UK, the integration of the suitability map, generated through the Analytical Hierarchy Process (AHP) by considering various weighted location criteria, with a map of suitable residential roads resulted in a new map (Fig. 14). This optimal suitability roads map designates a road network spanning 114.186 km as high-priority roads for charging point installation.

In the subsequent phase of the study, a robust methodology was applied to validate road selection and determine the ideal positions for on-street electric vehicle (EV) charging points. This validation process relied on the utilisation of Google Earth® and Google Street view. Google Earth®, developed by Google Inc., is a versatile geospatial tool that enables users to interact with a 3D Earth model using satellite imagery and aerial photos. It serves various purposes like geographical research, urban planning, and environmental monitoring. Users can explore specific locations, access historical imagery, and even view street-level scenes through Google Street View integration (Yu & Gong, 2012). This tool goes beyond basic mapping, allowing the visualization of geospatial data and custom map creation, making it invaluable for geospatial analysis and location-based research. Additionally, Google

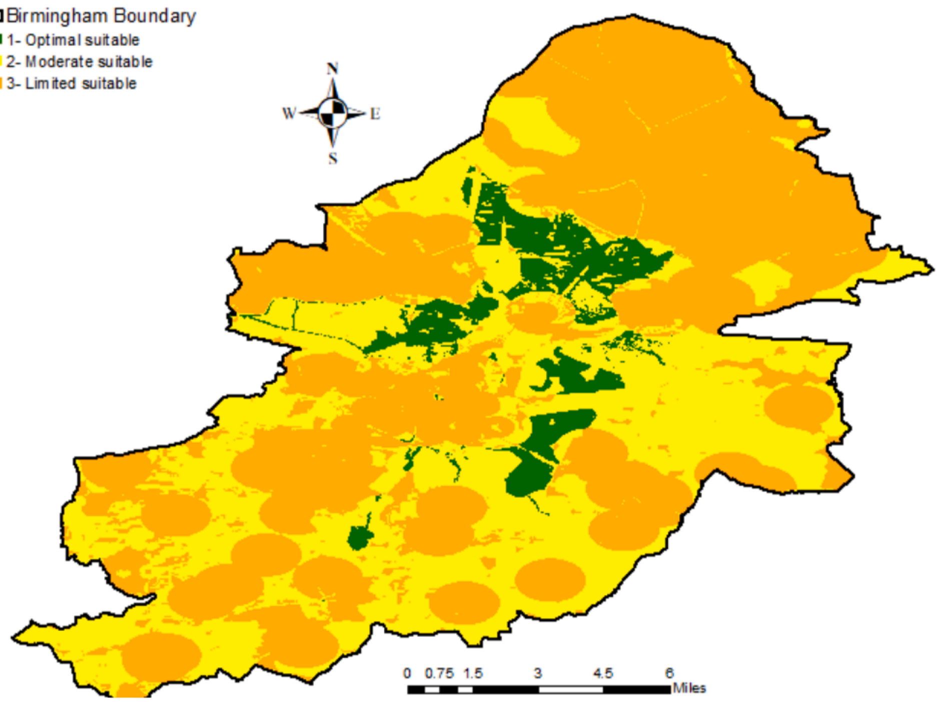

Fig. 13. Suitability map for Residential On-Street Electric Vehicle Charge Points (RO-EVCP).

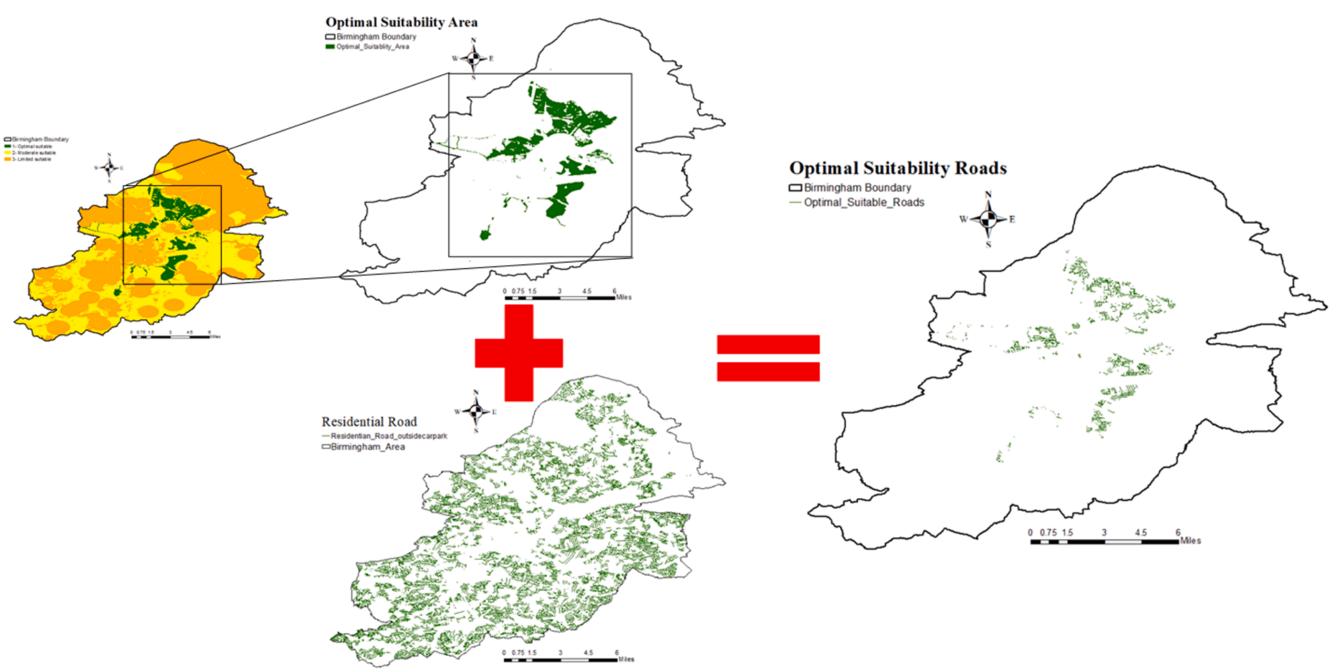

Fig. 14. Optimal suitability roads map.

Earth® seamlessly integrates with GIS through KML files, enhancing its capabilities (Bailey & Chen, 2011). The optimal GIS road map was converted into KML format to facilitate its retrieval in Google Earth Pro®. Initially, Google Earth Pro® was utilised for a comprehensive assessment of residential properties on streets designated as potential charging point sites. The primary aim was to ascertain whether these properties relied on street parking or possessed off-street parking facilities. Additionally, the feasibility of long-term car parking was evaluated, considering factors such as proximity to intersections, squares, and parking restrictions (e.g., zigzag lines, red routes, double yellow lines) (The Highway Code - Waiting and parking (238 to 252) - Guidance - GOV.UK). Streets where off-street parking predominated, aligning with home charging suitability, and also roads with no long-term parking potential, were excluded from further analysis. Subsequently, Google Street View served as a complementary tool, enhancing detail and accuracy, particularly in areas where Google Earth® imagery lacked granularity.

Google Street View, a feature of Google Maps, provides immersive 360-degree street-level imagery globally. It allows users to virtually navigate streets, neighborhoods, and landmarks, offering a realistic view of places they wish to visit. Google Street View is a valuable tool for navigation and location scouting (Ciepłuch et al., 2010). This supplementary validation step contributed to the refinement of findings, facilitating more informed decisions regarding residential EV charging point placement. The last step involves calculating the number of charging points needed for each street. This calculation is based on the visual inspection of parking spaces on the street, which calculates the average number of parking spaces available on each street. Using relevant literature, it is determined that each car needs 5.5 m of parking space, and it is recommended to install one charging point for every five cars (Birmingham City Council., 2021c; Karolemeas et al., 2021).

Appendix D offers a visual representation demonstrating the utilisation of Google Earth and Google Street View to validate the selection of streets for the placement of charging points. After conducting an extensive evaluation based on specific criteria and calculations, the total count of charging points for each street was established. A grand total of 1785 RO-EVCPs were earmarked for installation on high-priority streets. These charging points are spread across 261 distinct segments of streets, collectively covering a length of 52.32 km. Fig. 15 and Fig. 16 visually display the locations of these streets and charging points in the city of Birmingham.

This comprehensive data-driven methodology ensures a precise and evidence-based approach to road selection and the positioning of residential EV charging points on the street. By combining Google Earth® and Google Street View, this approach ensures that selected roads and charging locations align with real-world observations and practical considerations. This forms a strong foundation for making informed decisions in strategically deploying residential EV charging infrastructure. It's worth noting that certain variables, such as the location of lamp posts, income, and car ownership factors, and off-street parking availability, were initially left out of the GIS model. However, upon a thorough evaluation of streets for charger installation suitability, it became clear that a significant portion of streets identified as suitable by the GIS model in this study, which considered exclusion and suitability criteria, had substantial potential for hosting charging points. This highlights the model's effectiveness, comprehensiveness, and high accuracy. It also suggests that the model could be adapted for use in various urban settings beyond the scope of this research.

6. Discussion

The research aimed to determine the optimal locations for residential electric vehicle (EV) charging points in Birmingham, England using GIS-based geographic analysis. A thorough literature review was conducted to identify key factors, categorized into exclusion and suitability criteria. The Analytical Hierarchy Process (AHP) systematically assessed these criteria, with the distance to existing charging points, residential proximity, and air quality levels emerging as the most influential factors. This step highlighted the necessity of a strategic and environmentally conscious expansion of the EV charging network.

A tailored Geographic Information System (GIS) model was developed for Birmingham, incorporating factors such as accessibility, infrastructure, demographics, and environmental impact. The AHP method assigned appropriate weights to these factors, culminating in the creation of the "Electric Vehicle Charge Points Suitability Index (EVCP-SI) model." This model integrated weighted criteria to identify optimal locations for Residential On-Street Electric Vehicle Charging Points (RO-EVCPs), utilizing real-world data to ensure accuracy and relevance. The GIS-based model provided valuable insights into Birmingham's geographical and infrastructural complexities, aligning with existing literature that supports data-driven methodologies and multi-criteria selection processes in urban planning.

The study identified 261 street segments and 1785 specific locations in Birmingham as optimal for new residential on-street EV charging points. Factors considered included the potential for on-street parking and residents' reliance on such facilities. Proximity criteria, with walking distances of 2, 5, and 10 min from residential areas, projected coverage of 7.86 %, 14.71 %, and 23.72 % of the total residential area (18,017,313 m^2s). These findings represent a significant enhancement in the accessibility and availability of charging infrastructure, promoting EV adoption and sustainable urban mobility in Birmingham. (see Fig. 17).

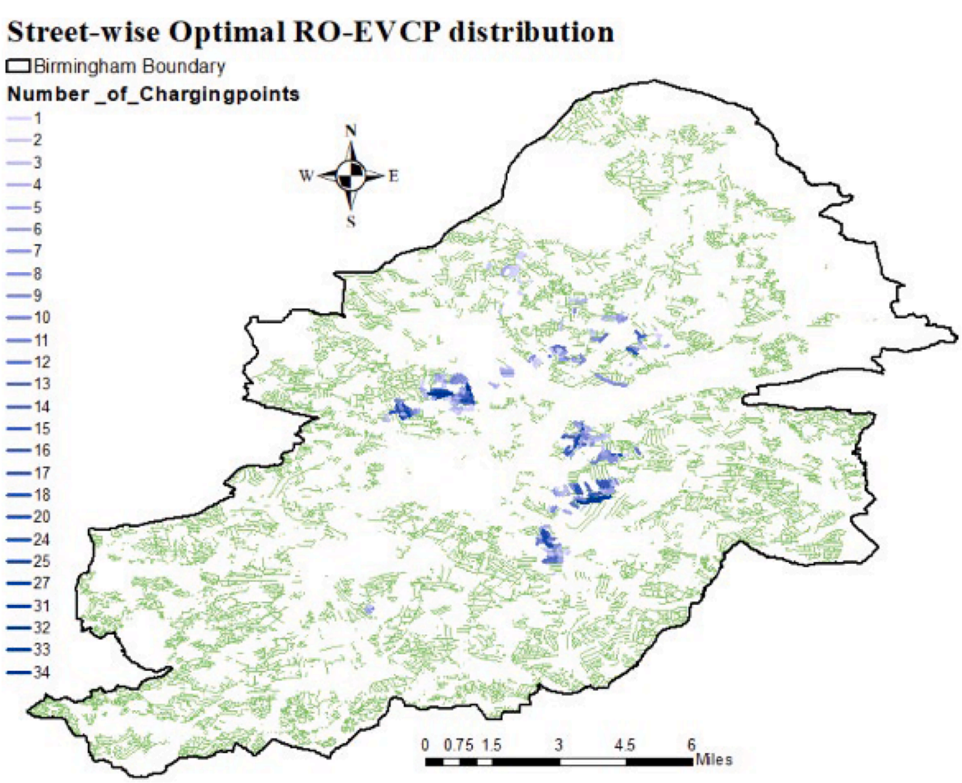

Fig. 15. Street-wise optimal RO-EVCP distribution in Birmingham, UK.

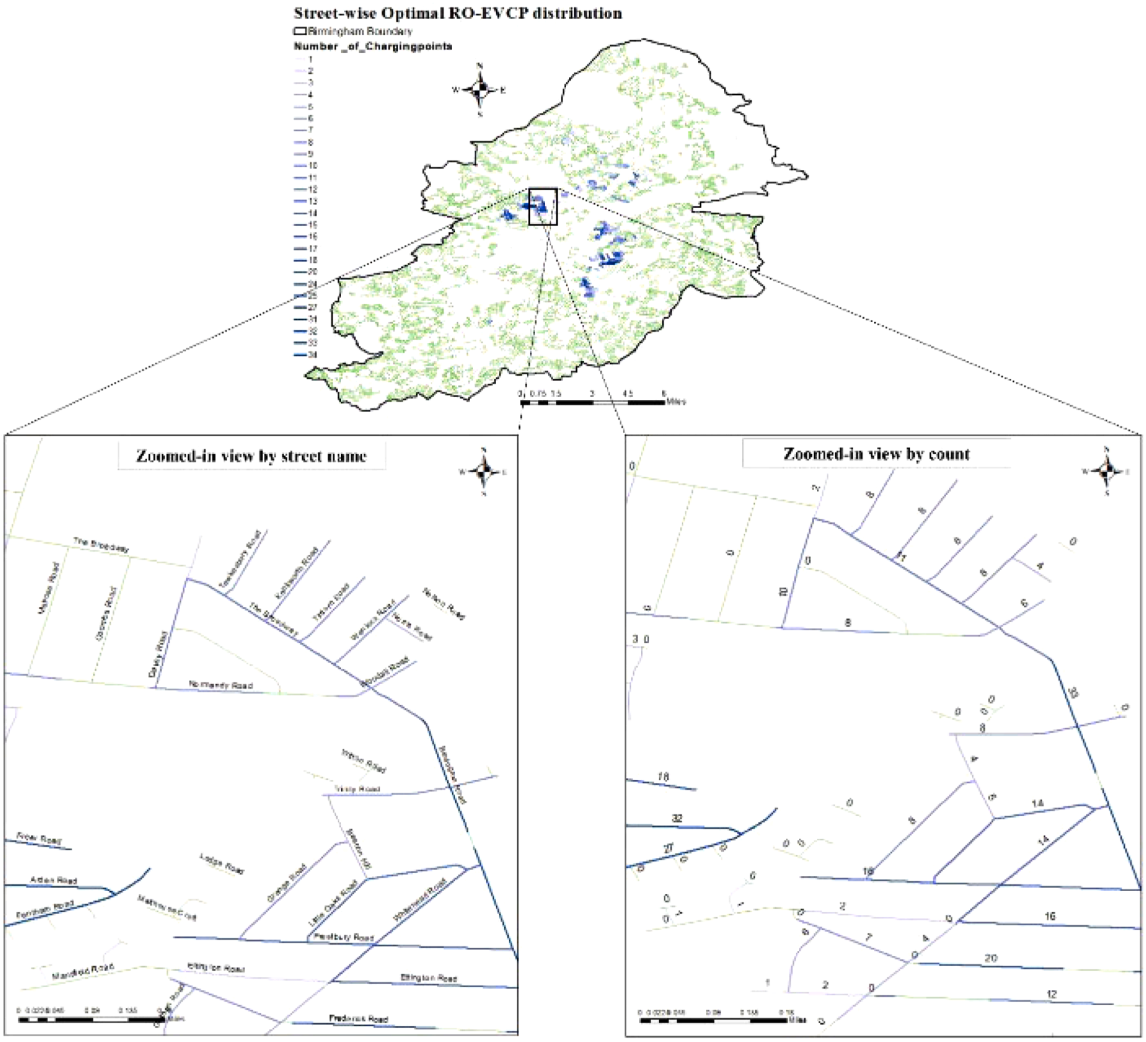

Fig. 16. Zoomed-in view of street-wise optimal RO-EVCP distribution.

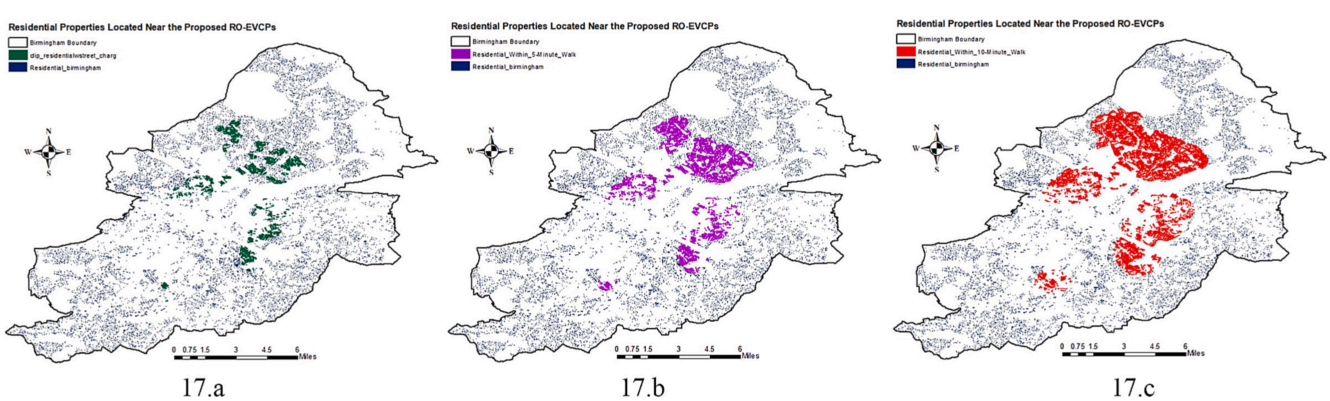

Fig. 17. Residential properties located near the proposed RO-EVCPs ((27.a): Within a 2-minute walk, (27.b): Within a 5-Minute Walk, (27.c): Within a 10-Minute Walk).

Strategically locating charging points within these walking distances greatly enhances the feasibility of electric vehicle usage for a significant portion of the residential population. This approach ensures that residents have convenient access to charging facilities without the need for extensive travel, thereby encouraging the adoption of electric vehicles as a viable and convenient mode of transportation. Additionally, the study's findings underscore the importance of strategically placing RO-EVCPs as valuable assets for electric vehicle charging services. By maximizing accessibility and coverage within residential areas, these charging points play a critical role in the city's electric vehicle infrastructure. Furthermore, Table 6 provides a detailed estimate of the area covered by residential buildings within walking distance, offering valuable insights for policymakers and urban planners dedicated to promoting sustainable transportation in Birmingham.

Table 6
Residential properties located near the proposed RO-EVCPs.

Figure Number	Walking Distance (Min)	Walking Distance (Meter)	Property Area(m2)	Percent of Total
26.a	Within a 2-Minute	160	1417,668	7.86 %
26.b	Within a 5-Minute	400	2651,820	14.71 %
26.c	Within a 10-Minute	800	4274,389	23.72 %

The findings of this study align closely with the existing body of literature on EV charging infrastructure, validating the methodologies and factors considered. Emphasis on proximity to existing charging infrastructure, residential access, and environmental factors resonates with prior research (Charly et al., 2023; Erbaş et al., 2018; Kaya et al., 2020; Mahdy et al., 2022). However, the study introduces a novel approach by assigning specific weights and priorities to these criteria, tailored to the unique context of Birmingham. New criteria such as "noise pollution" and "universal distribution of EVCPs for the disabled" highlight the study's commitment to inclusive design and environmental considerations.

Overall, the study's thorough review of previous research, meticulous factor selection, and use of efficient tools and methodologies contributed to generating practical and reliable results. The model's outcomes highlight high-priority locations primarily reliant on-street parking, reinforcing the importance of strategic and inclusive planning for EV infrastructure.

7. Conclusion

This study presents a comprehensive geospatial analysis aimed at identifying optimal locations for the installation of Residential On-Street Electric Vehicle Charging Points (RO-EVCPs) in Birmingham, UK. By utilizing a GIS-based model integrated with the Analytic Hierarchy Process (AHP), the research provides a data-driven framework to support urban planning decisions. Key findings from this study emphasize several critical factors influencing the placement of EV charging points, including Residential Proximity, Distance to Existing EVCPs, Population Density, Inclusive EVCP Distribution for Disabilities, EV-Prone Age Groups, Air Quality Levels, Noise Pollution, and Road Slope Compatibility. Notably, novel criteria such as 'Inclusive EVCP Distribution for Disabilities' and 'Noise Pollution' have not been previously explored in charging infrastructure research, whether focused on destination, en-route, or on-street charging. Additionally, this study is the first to examine 'EV-Prone Age Groups' and 'Air Quality Levels' in the context of Residential On-Street Charging Points. Among these, proximity to existing charging infrastructure, residential density, air quality levels, and noise pollution have emerged as the most influential factors. These factors were systematically weighted using the AHP method to develop the Electric Vehicle Charge Points Suitability Index (EVCP-SI). This index guided the identification of 261 optimal street segments and 1785 specific locations for RO-EVCPs across the city.

This study focuses on finding the best locations for Residential On-Street Electric Vehicle Charging Points in Birmingham, UK. A suitability map, created using the Analytical Hierarchy Process (AHP) with various weighted criteria, was combined with a map of suitable residential roads. This process resulted in a new map (Fig. 14) that identifies 114.186 km of road network as high-priority areas for installing charging points.

The analysis further revealed that 7.86 %, 14.71 %, and 23.72 % of Birmingham's residential areas are within 2-, 5-, and 10-minute walking distances from the proposed charging points, respectively, ensuring a high level of accessibility to residents and supporting widespread EV adoption. The model also incorporated environmental factors, underscoring the significance of placing EV charging points in areas where they can positively impact air quality and reduce noise pollution. A strong focus on inclusivity was maintained throughout the study, particularly by considering residential areas with limited access to off-street parking and ensuring that the infrastructure accommodates the needs of disabled users.

The GIS-based suitability map was validated using Google Earth® and Google Street View, enhancing its practical utility for urban planners and policymakers. Despite these valuable insights, the research acknowledges several limitations. The accuracy of the suitability map is dependent on the quality and availability of demographic, environmental, and infrastructure data, and any inaccuracies could affect the precision of the analysis. Additionally, subjectivity introduced by the AHP method in assigning weights to criteria may result in variations based on different expert judgments. Furthermore, the study did not incorporate dynamic modeling or real-time data to account for changes in urban dynamics, limiting its ability to adapt to evolving scenarios. Economic feasibility and regulatory aspects were also not comprehensively addressed, posing potential challenges for the deployment of the proposed infrastructure.

The study suggests promising directions for future research in electric vehicle (EV) infrastructure planning and deployment. Dynamic modeling techniques could be incorporated to consider evolving urban dynamics and population shifts, enabling a more adaptable strategy for EV infrastructure planning. Leveraging real-time data sources, such as traffic flow and air quality measurements, could enhance the accuracy of infrastructure placement models. Further research could explore methods to effectively integrate live data into decision-making processes. Additionally, alternative Multi-Criteria Decision Analysis (MCDA) methods could be explored to optimize EV infrastructure planning. Assessing the scalability and transferability of infrastructure planning models to other cities and regions, through comparative studies in diverse urban settings, can identify best practices and strategies for broader application.

CRediT authorship contribution statement

Milad Kazempour: Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Heba Sabboubeh:** Writing – review & editing, Supervision. **Kamyar Pirouz Moftakhari:** Writing – original draft, Conceptualization. **Reza Najafi:** Writing – original draft, Methodology, Formal analysis. **Gaetano Fusco:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2024.105988.

Data availability

Data will be made available on request.

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