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Unveiling city-scale urban roadside charging piles capacity: Geospatial knowledge-assisted small object detection and SDG 7-driven planning

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ABSTRACT

The rapid rise of electric vehicles (EVs) requires efficient detection and planning of urban roadside charging piles (RCPs) to support sustainable urban management. This study proposes a novel framework to optimize urban RCPs, integrating geospatial knowledge-assisted small object detection and Sustainable Development Goal 7 (SDG 7)-driven planning. We developed RCPs-YOLO, a tailored model that leverages geospatial knowledge to improve small object detection, achieving 89.8 % precision and 77.4 % mAP@0.5 in detecting RCPs from street view images, and a multi-line-of-sight method for precise geographic localization. Based on the EVs roadside charging demand across Nanjing Central Districts (NCDs) in year 2024, we suggest that the RCPs could support up to 301,537 kWh/day in NCDs. We develop four SDG 7-driven planning scenarios, including business-as-usual, equity-oriented, efficiency-oriented, and balanced development. Under these scenarios, the potential annual roadside charging capacity in NCDs by 2030 is approximately 85.8 GWh, 153.5 GWh, 103.2 GWh, and 148.3 GWh, respectively. Our findings suggest prioritizing the development of RCPs in newly developed downtown areas to promote equitable access and enhance energy efficiency. This approach offers a scalable, data-driven solution for urban planners aiming to advance progress toward SDG 7 and the development of smart cities.

1. Introduction

Urban power systems require secure and efficient operations to support the development of smart cities and to meet the increasing electricity demands (Qiu et al., 2024). Charging piles, a critical component of urban power infrastructure, can be installed in various locations, including roadside parking spaces (Charly et al., 2023). Although early electric vehicle (EV) infrastructure primarily consisted of centralized stations (Ji & Huang, 2018; Li et al., 2022a), these facilities often do not adequately address the needs of drivers requiring immediate charging during short-term parking (Ma & Fan, 2020). Roadside charging piles (RCPs) address this by providing accessible charging in existing parking spaces, thereby reducing land-use conflicts (Pu et al., 2025), and contributing to Sustainable Development Goal 7 (SDG 7) by facilitating the transition to clean energy. The projected growth of the global EV fleet to 17 million by 2024, with China expected to account for the majority of these vehicles (IEA, 2024), underscores the urgent need for expanded charging infrastructure. It is anticipated that 3.5 million EV charging stations will be installed in China by the end of 2024 (Xinhua, 2024). This rapid expansion underscores the critical role of charging infrastructure in facilitating the global transition to electric mobility and achieving sustainable urban development.

Effective planning of RCPs requires accurate data on their existing locations. However, public image datasets of RCPs are often lacking for urban infrastructure management (Bibri & Krogstie, 2017). This data gap hinders the equitable planning of new RCPs. The detection of RCPs is crucial, but their small size and widespread distribution pose challenges. While methods such as unmanned aerial vehicles (UAVs) and infrared imaging are often costly and inaccurate (Outay et al., 2020), street view images offer a cost-effective solution with broad coverage. We created the first city-scale RCP street-view dataset through manual annotation, which provides a foundational resource for RCP detection and planning.

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Nomenclature

EVs	Electric vehicles
RCPs	Roadside charging piles
SDG	Sustainable Development Goal
MLOS	Multi-line-of-sight
BAU	Business-as-Usual
EQ	Equity-Oriented
EF	Efficiency-Oriented
BD	Balanced Development
NCDs	Nanjing central districts
BSV	Baidu street view
LOS	line-of-sight

While the spatial optimization of public EV charging infrastructure has been extensively researched, the focus has been on centralized EV charging stations; the detection and planning of small-scale RCPs remain underexplored due to their dispersed distribution and data scarcity (Li et al., 2024). This gap hinders the development of efficient urban charging infrastructure, particularly in densely populated areas where space is limited and demand for charging is high. Governments worldwide are increasingly prioritizing the adoption of eco-friendly transportation and the development of associated infrastructure (He et al., 2016). SDG 7-driven planning, which integrates clean energy goals, offers a promising approach for RCP development, promoting equitable access and operational efficiency.

To fill these research gaps, we advance the RCPs planning efforts in three aspects, summarized below.

(1) We extend small object detection by incorporating geospatial knowledge of RCPs, offering a novel approach to urban infrastructure mapping, which provides a data basis for the planning of RCPs.
(2) We embed SDG 7 targets into the planning criteria, providing urban planners with a replicable blueprint for optimizing EV infrastructure.
(3) We estimate the potential roadside charging capacity of RCPs under four SDG 7-driven planning scenarios. We provide a framework for fine-grained planning and charging capacity estimation of RCPs, which is crucial for promoting RCP construction.

2. Literature review

2.1. Small object detection and localization in the power sector

Recent advances in small object detection have demonstrated transformative potential across critical power sector operations, including equipment inspection, fault diagnosis, and infrastructure monitoring (Liu et al., 2022). However, detecting small-scale equipment, such as charging piles, in complex urban environments remains challenging due to low feature saliency and background interference (Ou et al., 2023). Deep learning innovations, including improved Transformer modules (Zhao et al., 2024) and multiscale feature fusion and attention mechanisms (Xu et al., 2024), have improved detection accuracy. However, despite these advancements, challenges remain, including limitations in image resolution and high costs of specialized data acquisition systems (McEnroe et al., 2022).

Street view imagery is a cost-effective alternative that provides fine-grained spatial detail for urban detection (Han et al., 2023). To address challenges such as low feature saliency and background interference, innovations such as attention-enhanced detection and multi-task learning frameworks (Li et al., 2022a) have been developed, which improve feature representation and integrate geometric constraints. Despite these efforts, detecting and locating small-scale power equipment, such as RCPs, in urban settings continues to be challenging due to complex backgrounds and occlusion issues. Existing methods often struggle to achieve robust performance (Li et al., 2024), highlighting the need for further research to improve detection accuracy in such environments.

2.2. Optimized allocation of urban charging piles

Optimizing urban EV charging infrastructure requires balancing spatial, socio-economic and policy factors, especially with the rise of smart cities and SDG mandates (He et al., 2022). Existing studies have developed multi-criteria evaluation frameworks that integrate key factors such as population density, travel patterns, and the distribution of existing infrastructure. Spatial multi-criteria evaluation frameworks, combining GIS and AHP, are commonly used for infrastructure suitability analysis (Carra et al., 2022; Erbaş et al., 2018). Recent studies have focused on scenario-based optimization, such as corridor-specific planning (Erdoğan et al., 2022) and adaptive strategies for high-density areas (He et al., 2022). However, gaps remain in the precise location of charging piles and sustainable planning. Pu et al. (2025) employed deep learning segmentation and 3D geometric projection for charging space estimation but lacked specific location and long-term sustainability considerations.

2.3. Summary

The literature reveals two primary research gaps that this study aims to address. First, there is the challenge of accurately detecting and locating RCPs in complex urban environments due to issues like background interference and occlusion. Furthermore, there is a need for more precise and sustainable planning in the optimized allocation of urban charging infrastructure, addressing limitations in current methods that lack specific location and long-term sustainability considerations.

3. Materials and methods

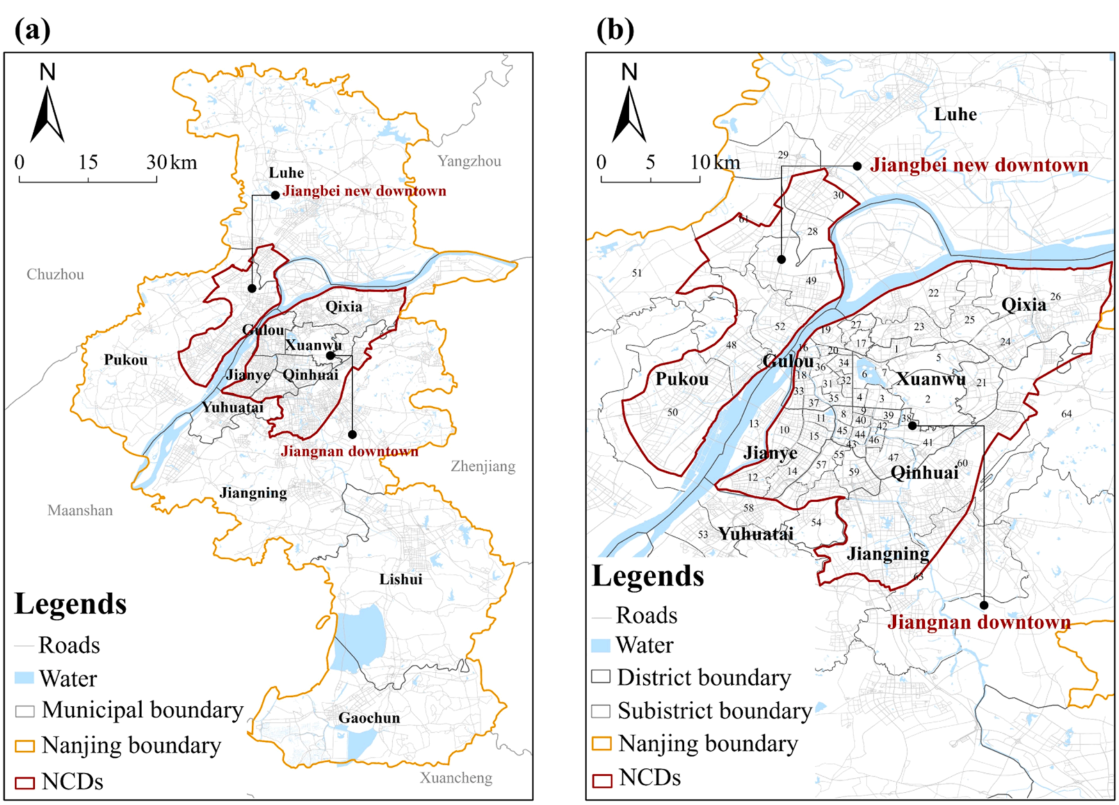
3.1. Study area

Nanjing is the capital of Jiangsu Province in eastern China. According to the “Nanjing Territorial Spatial Master Plan (2021–2035)” (Government, 2024), Nanjing Central Districts (NCDs) include the Jiangnan downtown and Jiangbei new downtown (Fig. 1).

The NCDs are critical transportation hubs with high traffic volumes and increasing demand for EV charging infrastructure due to their strategic location. The local government’s "14th Five-Year Plan for New Energy Vehicle Industry Development" promotes the installation of charging piles in roadside parking spaces, driving progress in sustainable energy and transportation through the deployment of RCPs. However, imbalances in RCP spatial distribution persist due to urban planning constraints, land-use conflicts, traffic dynamics, and uneven population distribution. Thus, developing robust methodologies for identifying and planning RCP locations is essential to support Nanjing’s sustainable development goals.

3.2. Research framework

Given the impact of current RCP distribution on future planning, our research framework integrates detection and planning methodologies through four components: (1) street view image collection, (2) a small object detection model for identifying RCPs, (3) the calculation of geographic coordinates for RCPs, and (4) SDG 7-driven planning for RCPs (Fig. 2). The first component involves the collection of street view images, which are essential for training the RCP detection model. The second component incorporates geospatial knowledge into a tailored detection model to address the limitations of conventional approaches in



1 Hongshan	9 Wulaocun	17 Xiaoshi	25 Yaohua	33 Jiangdong	41 Guanghualu	49 Yanjiang	57 Saihongqiao
2 Xiaolingwei	10 Xinglong	18 Rehenanlu	26 Qixia	34 Zhongyangmen	42 Daguanglu	50 Jiangpu	58 Xishanqiao
3 Meiyuanxincun	11 Mochouhu	19 Baotaqiao	27 Mufushan	35 Huaqiaolu	43 Zhonghuamen	51 Yongning	59 Ningnan
4 Xinjiekou	12 Shuangzha	20 Jianninglu	28 Xiejiadian	36 Yijiangmen	44 Fuzimiao	52 Taishan	60 Dongshan
5 Xuanwuhu	13 Jiangxinzhou	21 Maqun	29 Getang	37 Fenghuang	45 Shuangtang	53 Banqiao	61 Pancheng
6 Xuanwumen	14 Shazhou	22 Yanziqi	30 Dachang	38 Yueyahu	46 Qinhong	54 Tiexinqiao	62 Guli
7 Suojincun	15 Nanyuan	23 Maigaoqiao	31 Ninghailu	39 Ruijinlu	47 Honghua	55 Yuhuaxincun	63 Moling
8 Chaotiangong	16 Xiaguan	24 Xianlin	32 Hunanlu	40 Hongwulu	48 Dingshan	56 Meishan	64 Tangshan

Fig. 1. Study area: (a) Nanjing, China. (b) NCDs.

detecting small targets within urban environment from street view images. The third component applies a MLOS simulation, leveraging the detection results from the second component to calculate the geographic locations of existing RCPs. The fourth component involves developing an SDG 7-driven planning model, establishing objectives and constraints grounded in the core principles of SDG 7 to determine the optimal spatial distribution and estimate potential roadside capacity of RCPs.

3.3. Baidu street view images collection

To construct Baidu Street View (BSV) image datasets for training the RCP detection model, road networks across NCDs were extracted from OpenStreetMap (OSM, https://www.openstreetmap.org/). These networks were then sampled at 15-meter intervals, generating 2213,013 sample points (Fig. 3(a)). Using Baidu Maps API, multi-orientation street view imagery (including front, back, left, and right views) was retrieved, along with its associated metadata (Fig. 3(b)). The acquired images underwent cylindrical equidistant projection to produce standardized 360° panoramas with a resolution of 1024 × 512 pixels (Zhong et al., 2021). Each panoramic image was oriented so that its central axis orientation aligned with the corresponding road direction angle (Fig. 3 (c)).

The construction of the RCP dataset posed significant challenges due to the small size and low occurrence frequency of RCPs in street view imagery. As small objects, RCPs are widely dispersed in the city (Zhang et al., 2023) and are frequently obscured by vehicles, pedestrians, or urban clutter in BSV images. Moreover, their sparse distribution necessitated the screening of massive volumes of data. We implemented a two-stage annotation process: (1) Pre-screening: We prioritized BSV images near known EV hotspots (e.g., commercial districts, transportation hubs) (Ji & Huang, 2018) to increase the likelihood of finding RCP-positive samples. (2) Annotation verification: We labeled RCPs under strict visibility criteria, including bounding box integrity, and the absence of severe occlusion. We finally collected and constructed a sample dataset of RCP-containing BSV images and manually screened 706 RCP-containing images from 35,914 BSV images captured between 2020 and 2023 across 14 major Chinese cities (e.g., Beijing, Shanghai, and Guangzhou).

3.4. RCPs-YOLO model for RCP detection

YOLOv11, while effective for general object detection, struggles with small-scale RCPs due to redundant deep feature extraction and limited spatial reasoning. We propose RCPs-YOLO, which introduces a key

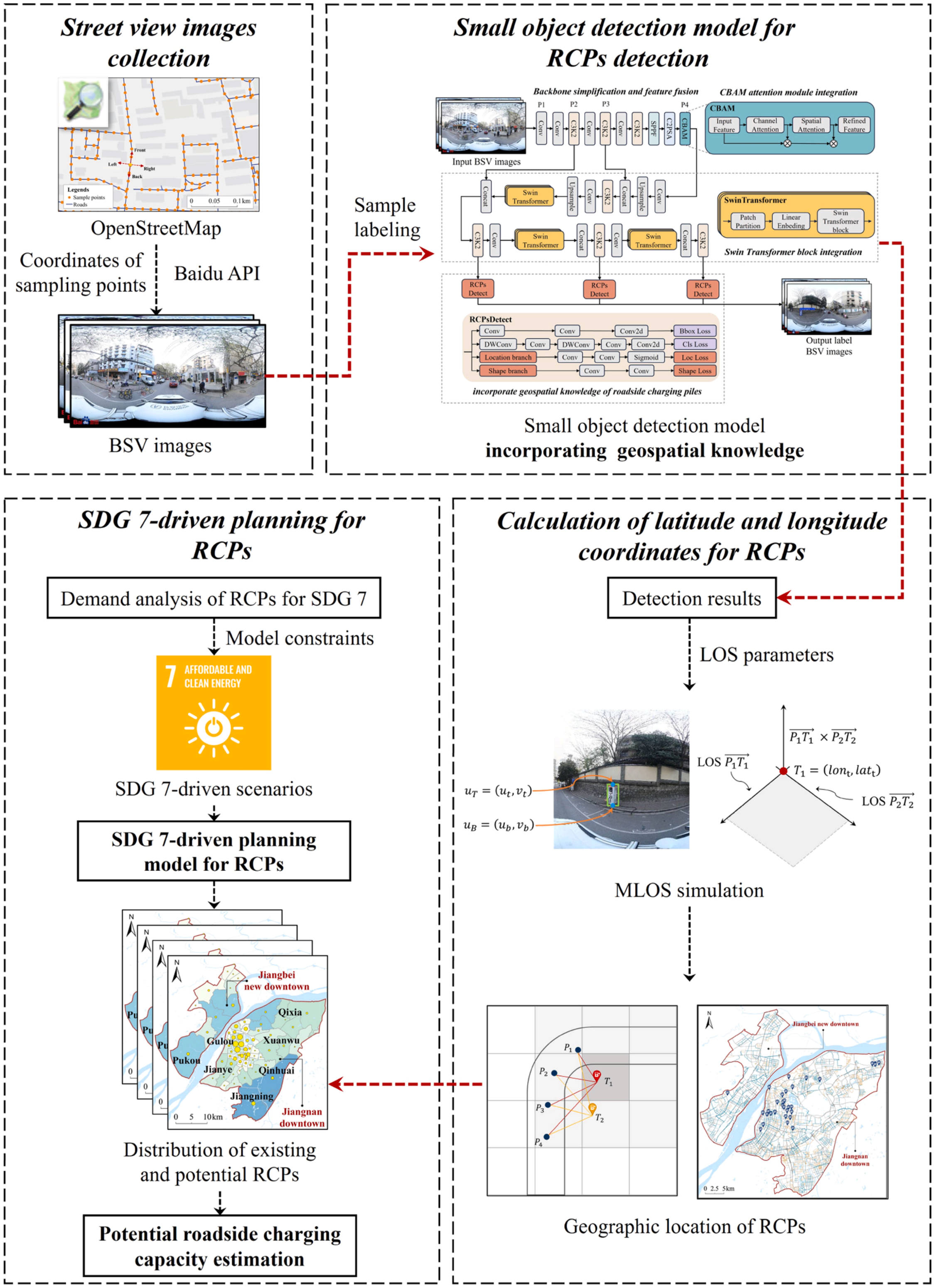


Fig. 2. Framework of detection, locating and SDG 7-driven planning of RCPs.

innovation: the integration of geospatial knowledge to enhance small object detection. Fig. 4 shows the modifications made to RCPs-YOLO based on YOLOv11, highlighted with red dashed boxes.

(1) Geospatial knowledge head (RCPsDetect): We replace YOLOv11's default detection head with RCPsDetect, which leverages a geospatial knowledge graph as a source of prior knowledge. This graph captures RCPs' spatial relationships with urban entities (e.g., roads, parking spaces) and geometric attributes. RCPsDetect features two branches, the location-aware branch uses the knowledge graph to generate confidence maps for likely RCP locations, and the shape-refinement branch adjusts bounding boxes based on RCP geometric properties (Fig. 5).

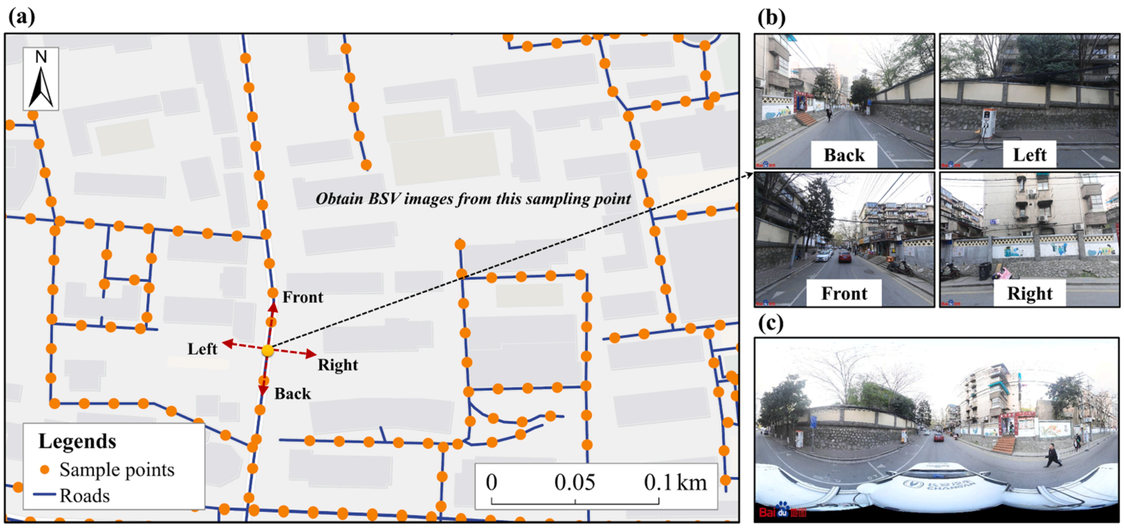


Fig. 3. Schematic diagram of BSV images collection: (a) Acquired BSV images using sample points (b) BSV images obtained from four directions at the yellow sampling point (c) Corresponding 360° panorama image (Source from: OpenStreetMap, https://www.openstreetmap.org/).

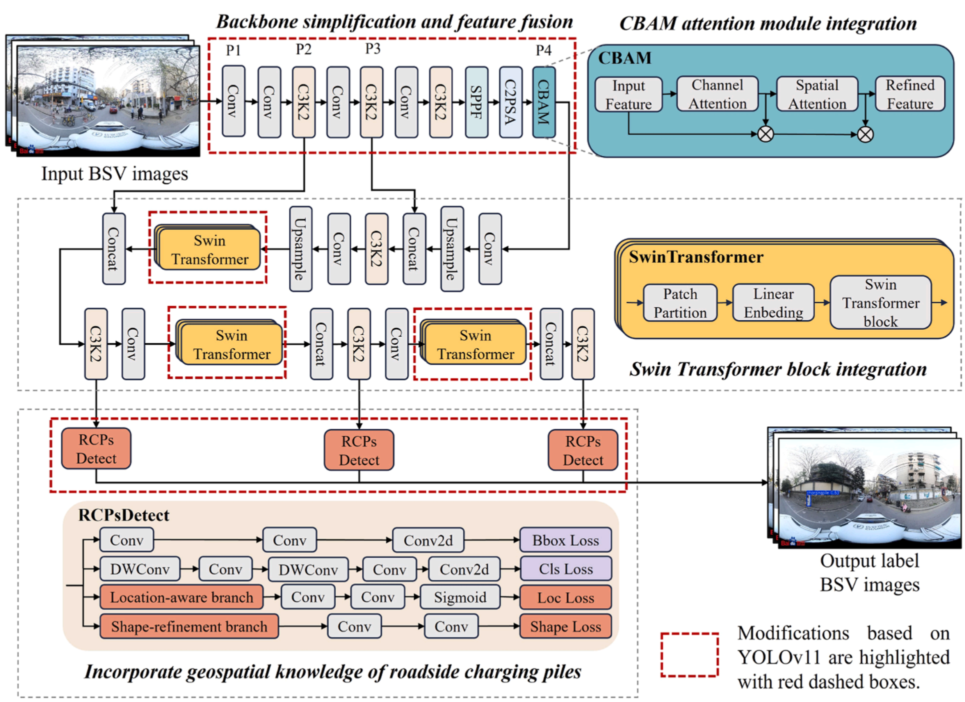


Fig. 4. Architecture of the RCPs-YOLO network.

The knowledge graph is built through a semi-automatic process. First, we annotate street view images to identify RCPs; next, we define their spatial relationships and integrate this information into the graph. The location-aware branch utilizes the knowledge graph to predict high-probability zones for RCPs, fusing this spatial information with the feature maps from the backbone network, while the shape-refinement branch leverages geometric attributes from the knowledge graph to adjust bounding box predictions, ensuring alignment with typical RCP dimensions.

(2) Backbone simplification: We simplify the backbone by removing the P5 layer and fusing the P4, P3, and P2 feature maps. This modification reduces the number of model parameters while preserving details crucial for small object detection.

(3) CBAM integration: A Convolutional Block Attention Module (CBAM) is integrated after the SPPF block to improve feature extraction for small objects in complex scenes.

(4) Swin Transformer integration: Three Swin Transformer modules are incorporated into each detection head to capture multi-scale features effectively.

3.5. The calculation of geographic coordinates for RCPs

We performed automatic geographic localization of RCPs using a MLOS simulation method designed with reference to the adaptive constrained Line of Bearing (LOB) localization method proposed by Li et al. (2022a). Additionally, we introduce a vector cross-product method to eliminate erroneous MLOS intersections. The main process consists of three stages: (1) MLOS simulation based on detection results, (2)

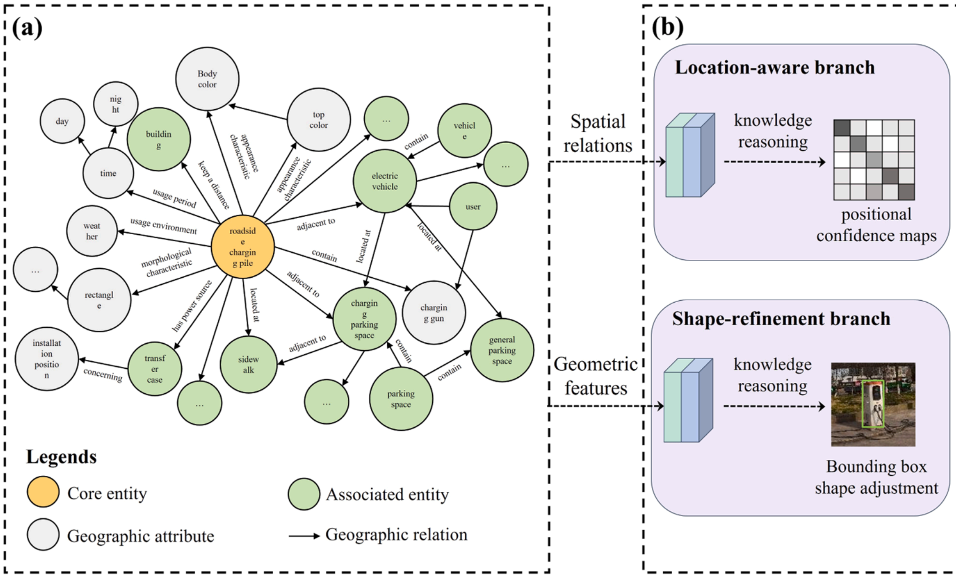


Fig. 5. Schematic diagram of RCPsDetect head architecture. (a) Geospatial knowledge graph of RCPs (b) Two specialized branches in RCPsDetect.

elimination of erroneous intersections occurring behind the LOS, and (3) LOS calculation using grid partitioning and spatial clustering (Fig. 6).

The MLOS method is based on geometric triangulation principles, which use multiple viewpoints to determine the latitude and longitude of charging piles (Li et al., 2022a). After detecting RCPs using the RCPs-YOLO model, the pixel coordinates of the bottom and top centers of the bounding box u_B, u_T are extracted from panoramic images, corresponding to the pile's geographic locations (Fig. 7 (a-c)). Each viewpoint generates a LOS using azimuth and elevation angles $(\theta_b, \theta_t, \phi_b, \phi_t)$ relative to the principal point h_p (Fig. 7 (d-e)). The intersections of multiple LOSs determine the RCP's location.

To ensure accuracy, a vector cross-product method is used to remove erroneous intersections located behind the line of sight, thereby retaining only valid, forward-facing intersections. This vector cross-product technique represents an improvement over the LOB method in (Li et al., 2022a), as it more effectively filters invalid intersections behind the viewpoints, leading to reduced localization errors in dense urban settings. The roadway is then divided into grids to reduce

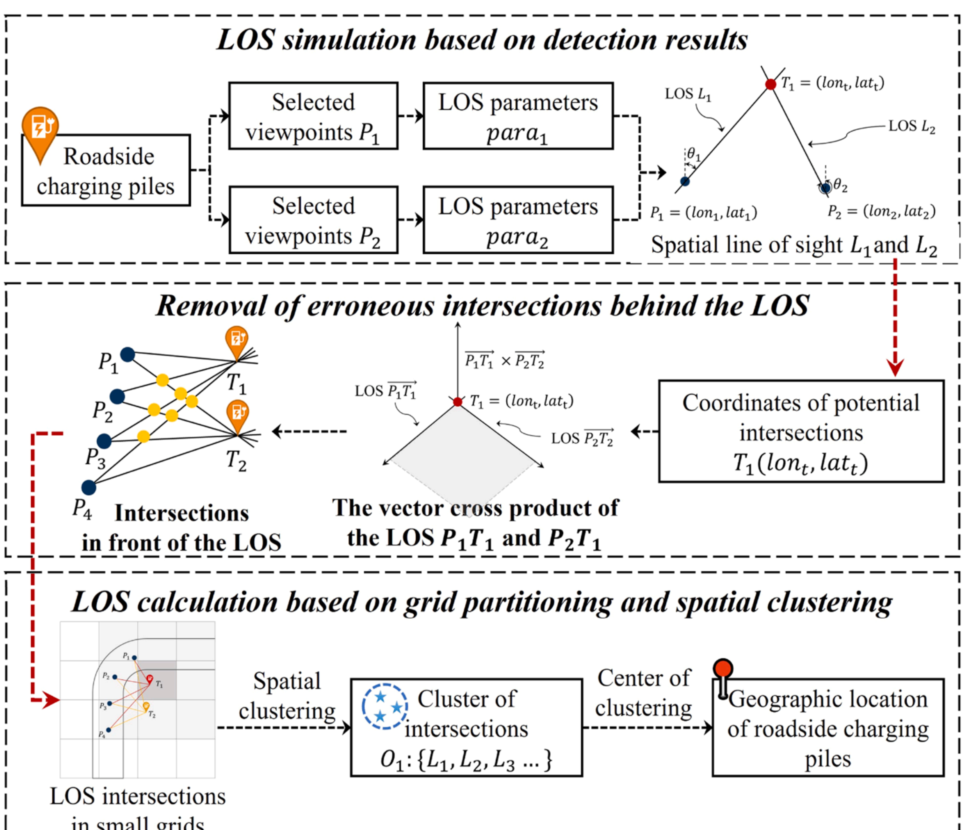


Fig. 6. Flowchart for automatic geographic localization of RCPs.

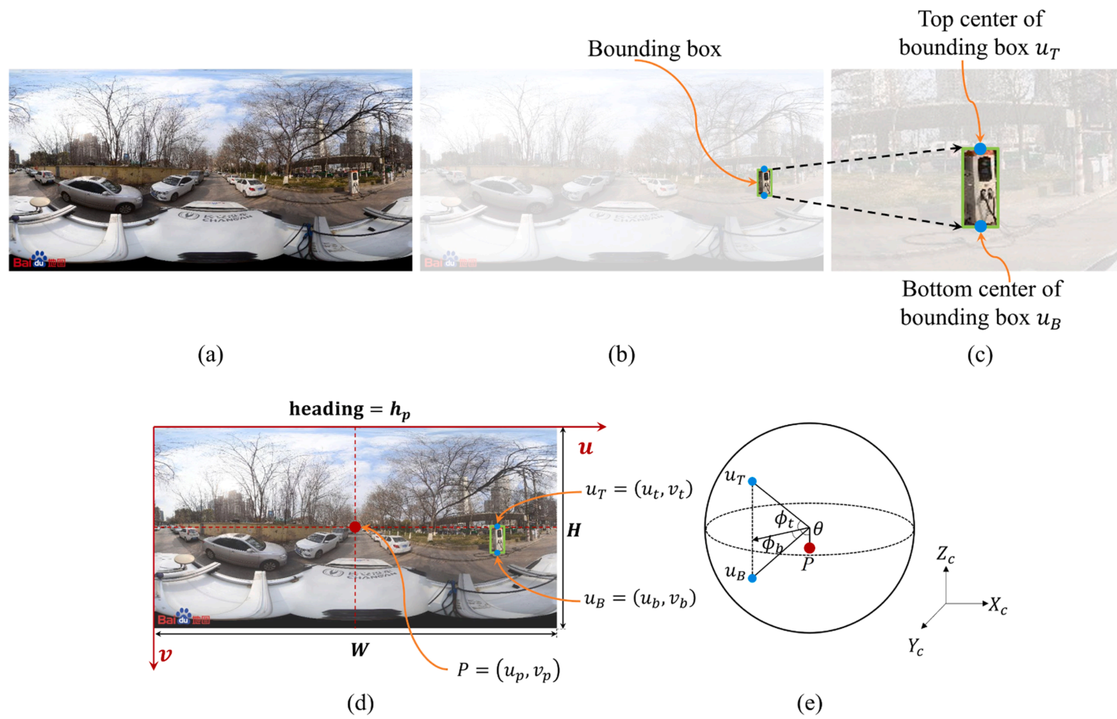


Fig. 7. Schematic diagram of the bounding box for RCP: (a) Street view images (b) Bounding box (c) Image enlargement (d) Obtain LOS parameters from street view images (e) Corresponding spherical coordinates.

computational complexity. The MLOS intersections are clustered to identify RCP locations, and the center of cluster is designated as final coordinates.

3.6. SDG 7-driven planning for RCPs

The SDG 7-driven planning model integrates the United Nations' Sustainable Development Goal 7 (SDG 7), which emphasizes affordable and clean energy, into the spatial planning of RCPs. SDG 7 focuses on energy equity (SDG 7.1), optimizing energy structure (SDG 7.2), and enhancing energy efficiency (SDG 7.3). This model maps these sustainability targets to RCP planning by optimizing charging accessibility and operational efficiency, thereby providing a replicable blueprint for urban EV infrastructure.

The model leverages governmental EV policies and user charging behavior to determine demand, ensuring practical applicability. Four planning scenarios, including Business-as-Usual (BAU), Equity-Oriented (EQ), Efficiency-Oriented (EF), and Balanced Development (BD), project RCP allocation from 2025 to 2030, each aligned with SDG 7 objectives.

3.6.1. Demand analysis of RCPs for SDG 7

Demand analysis for RCPs forecasts spatial requirements to support SDG 7-driven planning, focusing on equitable and efficient charging infrastructure, we estimate RCP demand by estimating the EV purchase demand and daily usage demand, driven by population density in urban China (Ma & Fan, 2020), where limited private chargers increase reliance on public infrastructure (He et al., 2016; Wang et al., 2021). This correlation establishes population density as a key criterion for projecting EV adoption over a five-year horizon.

To estimate the EV purchase demand (D_p), we define the population count in the i-th region (N_i), the driving license ownership ratio (P_{lic}), and probability of users intending to purchase EVs (P). The value for P is set to 0.13, based on the findings of He et al. (2022). D_p is then calculated as:

$$D_p = N_i \times P \times P_{lic} \tag{1}$$

To estimate the daily utilization demand for RCPs ($D_{planning}$), we define the daily charging probability for EVs C_d, the probability of users utilizing RCPs for charging P_{pub}. Based on prior studies, C_d is set to 0.33 (Wang et al., 2021), and P_{pub} is set to 0.5 (He et al., 2022). $D_{planning}$ is then calculated using the formula from He et al. (2022):

$$D_{planning} = D_p \times C_d \times P_{pub} \tag{2}$$

3.6.2. SDG 7-driven planning scenarios for RCPs

We developed four planning scenarios (BAU, EQ, EF, and BD) to forecast the spatial allocation of urban RCPs from 2025 to 2030. Each scenario is defined by a unique configuration of parameters governing charging accessibility and efficiency, aligning with the sustainability goals of SDG 7 (see Table 1).

3.6.3. SDG 7-driven planning model for RCPs

The SDG 7-driven planning model optimizes the RCP placement to minimize charging demand gaps and travel distances, thereby aligning with SDG 7's mandate for equitable clean energy access. The study area is divided into 1 × 1 km grids as the smallest spatial units, with each grid's center is designated as a demand point to represent localized charging needs. The allocation of RCPs requires a comprehensive evaluation of surrounding site conditions and traffic patterns. RCP installation is restricted to roadside parking spaces on residential, secondary, tertiary, and service roads. This excludes internal community roads and high-grade roads (e.g., primary roads and expressways) in order to comply with traffic and zoning regulations.

The parameters utilized in the SDG 7-driven planning model are listed in Table 2.

The SDG 7-driven planning model is formulated as follows:

$$Minimize\left(\sum_{i\in I} s_i + \sum_{i\in I, j\in J} n_{ij} d_{ij} + \sum_{j\in J} C_j a_j\right) \tag{3}$$

subject to:

$$n_{ij}, s_i \geq 0, \quad \forall i \in I, j \in J \tag{4}$$

Table 1
SDG 7-driven planning scenario for RCPs in 2030.

Scenario	Scenario Description	Direction of Parameters Adjustment
BAU Scenario	This scenario represents a continuation of current urban policies and serves as a baseline for comparative analysis.	Parameters are configured according to existing municipal government documents and planning guidelines.
EQ Scenario	This scenario prioritizes SDG 7.1 by ensuring equitable charging access across all demand points.	The primary adjustment is an increase in the total number of RCPs to enhance coverage.
EF Scenario	This scenario focuses on SDG 7.3 by optimizing both accessibility and resource utilization efficiency.	Adjustments focus on reducing the distance between demand points and RCPs while enhancing charging efficiency.
BD Scenario	This scenario creates a synergistic balance among SDGs 7.1 and 7.3 by coordinating charging equity with efficiency.	Parameters are adjusted to simultaneously improve both RCP accessibility and operational efficiency.

Table 2
Parameters of the SDG 7-driven planning model.

Parameter	Definition
I	Set of demand points i
J	Set of candidates charging locations j
s_i	Charging demand gap at demand point i
h_i	Estimated number of EV with charging demand at demand point i per day
n_{ij}	Number of EVs allocated from demand point i to RCP j
d_{ij}	Distance from demand point i to RCP j
d_{max}	Max distance from demand point i to RCP j
J_i	Set of charging locations within the coverage radius of demand point i
μ	Number of EVs charged per day by each RCP
e_j	Existing RCPs at location j
a_j	Additional RCPs to be deployed at site
k_{min}	Minimum required number of new RCPs
k_{max}	Maximum required number of new RCPs
J_r	Sets of all candidate sites located in residential zones
J_c	Sets of all candidate sites located in commercial zones
C_j	Maintenance cost for RCP at location j

$$\sum_{j\in J_i} n_{ij} + s_i = h_i, \quad \forall i \in I \tag{5}$$

$$\sum_{i\in I} n_{ij} \le \sum \mu\left(e_j + a_j\right), \quad \forall j \in J \tag{6}$$

$$1 \le a_j \le 3 \tag{7}$$

$$k_{min} \le \sum_{j\in J} a_j \le k_{max} \tag{8}$$

$$d_{ij} \le d_{max} \tag{9}$$

$$J = J_r \cup J_c \tag{10}$$

The objectives of the model (Eq. (3)) are threefold: to minimize the charging demand gap, to reduce travel distances to RCPs and to minimize maintenance costs. The primary objective reduces unmet EV charging demand, while the secondary objective enhances accessibility by minimizing distances from demand points to RCPs, and the tertiary objective is to incorporates maintenance costs, which are typically determined to be 2 % of the construction cost (Chen et al., 2023; Zhang et al., 2018). Five constraints are incorporated: (1) Demand allocation constraint: This constraint allocates EV charging demand to RCPs within a coverage radius (Fig. 8), with unmet demand defining the gap. (2) Coverage constraint: A service radius is defined based on governmental guidelines and previous studies. This radius represents the maximum distance between demand points and RCPs (Guo et al., 2018; He et al., 2016). (3) This constraint limits charging capacity constraint: Limits daily EV charging capacity per pile. (4) Quantity constraint: This constraint restricts each site to 1–3 RCPs to maintain grid stability, per China's EV charging standards (StateGrid, 2016). (5) Land-use zoning constraint: Limits RCP sites to residential and commercial zones, disregarding demand points outside these areas. This is done to comply with regulations and enhance deployment feasibility (Charly et al., 2023; Csiszár et al., 2019; Pu et al., 2025). We assume that electricity grid load is addressed through using charging scheduling on regional clean energy power supply network management (Zhou et al., 2025), and using distributed generators to reduce negative impacts on the electricity grid (Aggarwal et al., 2024). Therefore, electricity grid load is not considered in the model. This study does not differentiate between types of RCPs.

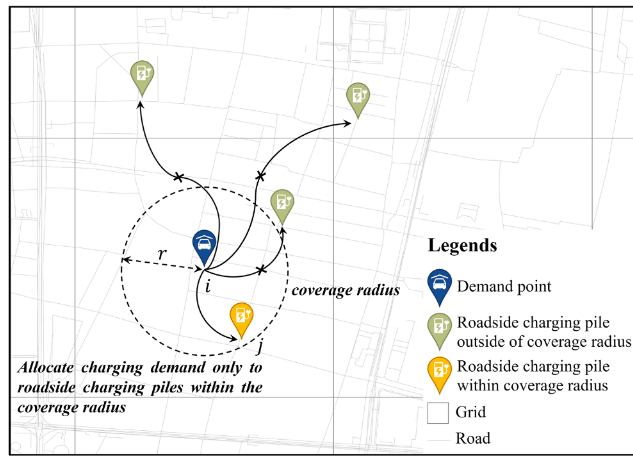


Fig. 8. Schematic diagram of allocating roadside charging demand from a demand point to RCPs within a specified radius.

3.7. Roadside charging capacity estimation

Based on the EV charging demand D across NCDs, we estimated the roadside charging capacity based on demand by using the number of EVs in NCDs (N_{EV}). For example, we utilized Nanjing's 2024 government-reported EV ownership statistics (Nanjing Municipal Bureau of Statistics, 2025) for estimation.

$$D = N_{EV} \times C_d \times P_{pub} \tag{11}$$

The values of C_d and P_{pub} are set as specified in Section 3.6.1.

We then estimated the roadside charging capacity based on demand E_d in each district. We established the energy per charging session for EVs (E_{charge}) as 48 kWh, based on (Wang et al., 2019).

$$E_d = \sum_{i=1}^{365} D \times E_{charge} \tag{12}$$

where i represents the day ($i = 1,2,3,\ldots,365$). We assume that the RCPs in NCDs exclusively operate in direct current (DC) fast charging mode, and the initial state of charge of EVs upon arrival at the RCPs is disregarded for calculation simplification.

Given that the planning scenarios and their parameter settings are derived from the roadside charging demand assumptions in Section 3.6.1, we estimated the potential annual roadside charging capacity E_p in each district utilizing the number of RCPs (N_{pile}) and the number of EV charges per RCP per day (μ).

$$E_p = \sum_{i=1}^{365} N_{pile} \times E_{charge} \times \mu \tag{13}$$

4. Results

4.1. Results and analysis of RCPs detection and localization

Following the detection of RCPs in NCDs using the RCPs-YOLO model, its detection performance was subsequently evaluated. The evaluation employed four key metrics commonly used in object detection: precision, recall, F1-score, and mean average precision (mAP). Comparative experiments with YOLOv8s and YOLOv11s, conducted on the same dataset and computing platform with optimized hyperparameters, validate RCPs-YOLO's superior accuracy and efficiency (Table 3).

According to the results in Table 3, compared to YOLOv11s, RCPs-YOLO achieves improvements of 2.6 % in precision, 2.8 % in recall, 3 % in F1-score, and 1.9 % in mAP@0.5, while reducing parameters by 61.7 %. These gains stem from incorporation of the geospatial knowledge head, which leverages prior knowledge of RCP locations and structures, the CBAM attention module for enhanced feature learning, and the Swin Transformer's hierarchical windowing to address occlusions. The reduced parameter count enhances efficiency, making RCPs-YOLO suitable for resource-constrained environments while maintaining robust detection of small objects like RCPs.

To validate the geographic localization accuracy of our MLOS method, we refer to the evaluation results reported (Li et al., 2022a). Our MLOS method is grounded in the rigorously validated adaptive Line-of-Bearing (LOB) framework, which demonstrated a recall of at least 88 % and a precision of at least 92 % for detecting pole-shaped infrastructure (e.g., traffic signs and utility poles) across different threshold settings. Given that RCPs exhibit physical characteristics similar to these vertical pole structures and considering the comparable urban environments of Nanjing and Changzhou in Jiangsu Province, our approach integrates vector cross-product validation to enhance robustness by eliminating erroneous intersections that indicate backward-facing orientations. These methodological refinements, coupled with the benchmark accuracy established by Li et al. (2022a), demonstrate that the geographic localization accuracy of our MLOS method is comparable to that reported in their study.

Based on the central pixel positions of the bounding boxes for RCPs obtained from the detection results, and incorporating the LOS parameters, we calculated the MLOS intersection points. Cluster analysis was then applied to filter eligible viewpoints, leading to the determination of the geographic locations of RCPs in NCDs.

Fig. 9 shows the spatial distribution of RCPs in NCDs, highlighting the specific locations of these piles in two representative sites. RCPs exhibit clustered distribution patterns in Jiangnan downtown (Fig. 9(a)). The intricate road network and high traffic volumes in Jiangnan downtown reflect high transportation activity, which directly correlates with residents' urgent demand for accessible charging infrastructure. Emerging urban districts developed in recent years, such as Jiangbei new downtown and the southeastern sector of Jiangnan downtown, currently exhibit a scarcity of RCPs, necessitating prioritized deployment planning in these areas. Furthermore, temporal limitations of street view images may result in undetected newly installed RCPs in these areas. Future research can integrate multi-source geospatial data to mitigate this methodological constraint.

Moreover, our findings reveal that RCPs are mainly deployed in residential roads (Fig. 9(b)) and tertiary roads (Fig. 9(c)), a consequence of urban planning strategies that primarily allocate charging piles to high-density residential areas, transportation hubs, and commercial centers, thereby achieving economies of scale in management and maintenance. Simultaneously, high-traffic and densely populated areas naturally emerge as preferred locations for charging pile allocation, as they accommodate substantial EV user demand.

Table 3
Performance comparison of RCPs-YOLO and other models.

Models	Precision	Recall	F1-score	mAP@0.5	Parameters
YOLOv8s	0.866	0.639	0.73	0.767	11.1 M
YOLOv11s	0.872	0.603	0.71	0.755	9.4 M
RCPs-YOLO	**0.898**	**0.631**	**0.74**	**0.774**	**3.6 M**

4.2. SDG 7-driven planning results and analysis of RCPs

4.2.1. Parameter settings of spatial planning model for RCPs

This section details the implementation of the spatial planning model for RCPs in Nanjing. The population data utilized in the model were sourced from the 2024 WorldPop gridded population dataset, which has a 100-meter spatial resolution (https://hub.worldpop.org/). The urban land use zoning data for Nanjing is sourced from the 2022 urban land use data provided by Essential Urban Land Use Category-China (EULUC-China 2.0) (Li et al., 2025). Table 4 presents parameter configurations for the BAU scenario, which were set based on the actual situation in NCDs. These parameter values were derived from municipal policy documents and planning guidelines for public charging infrastructure.

Building upon the BAU baseline, Table 5 compares parameter adjustments across three alternative scenarios. Among them, the EQ scenario prioritizes expanding service capacity by increasing daily EV charging capacity per pile and raising allocation quantity thresholds, the EF scenario emphasizes intensive resource utilization by reducing the distance between demand points and RCPs while improving charging efficiency, and the BD scenario balances accessibility-efficiency tradeoffs through moderate parameter tuning.

4.2.2. Spatial distribution results and analysis of potential RCPs

The model was solved using CPLEX 12.10 and Arcpy 3.0. Optimal solutions indicate allocations of 1224 (BAU), 2192 (EQ), 1177 (EF), and 1693 (BD) additional RCPs. Fig. 10 illustrates the spatial distribution of existing and potential RCPs across scenarios. The distribution of potential RCPs is predominantly concentrated in commercial and residential zones, exhibiting greater allocations in newly developing districts (e.g., Pukou and Jianye Districts), particularly in high-demand areas. Conversely, scenic areas (e.g., Xuanwu District) are allocated fewer RCPs to maintain traffic order.

In the BAU scenario, RCP allocation aligns with Nanjing Municipal Government planning documents (Fig. 10(a)). However, this scenario does not adequately address charging equity and efficiency considerations, potentially exacerbating spatial imbalances and posing risks of service inadequacy in emerging development zones.

The EQ scenario exhibits more equitable RCP distribution across all regions compared to BAU, characterized by increased allocations in established urban areas (e.g., Gulou District) (Fig. 10(b)). This pattern stems from a deliberate emphasis on spatial equity, resulting in additional RCPs in high-traffic commercial districts, transportation hubs, and newly developed urban areas. While improving accessibility, this may strain grid infrastructure without targeted upgrades for charging technology, challenging SDG 7.3.

The EF scenario shows minimal RCP expansion, emphasizing efficient utilization (Fig. 10(c)), characterized by the fewest deployments across three sample districts. This outcome reflects a strategy focused on optimizing energy use and reducing waste, aligning closely with SDG 7.3. However, the limited expansion is driven by prioritizing efficiency over broader coverage, which may risk inadequate service provision in growing areas, potentially compromising SDG 7.1.

Compared to BAU, the BD scenario demonstrates moderate RCP growth (Fig. 10(d)). Older districts (e.g., predominantly residential Gulou District) receive allocations that address charging difficulties in

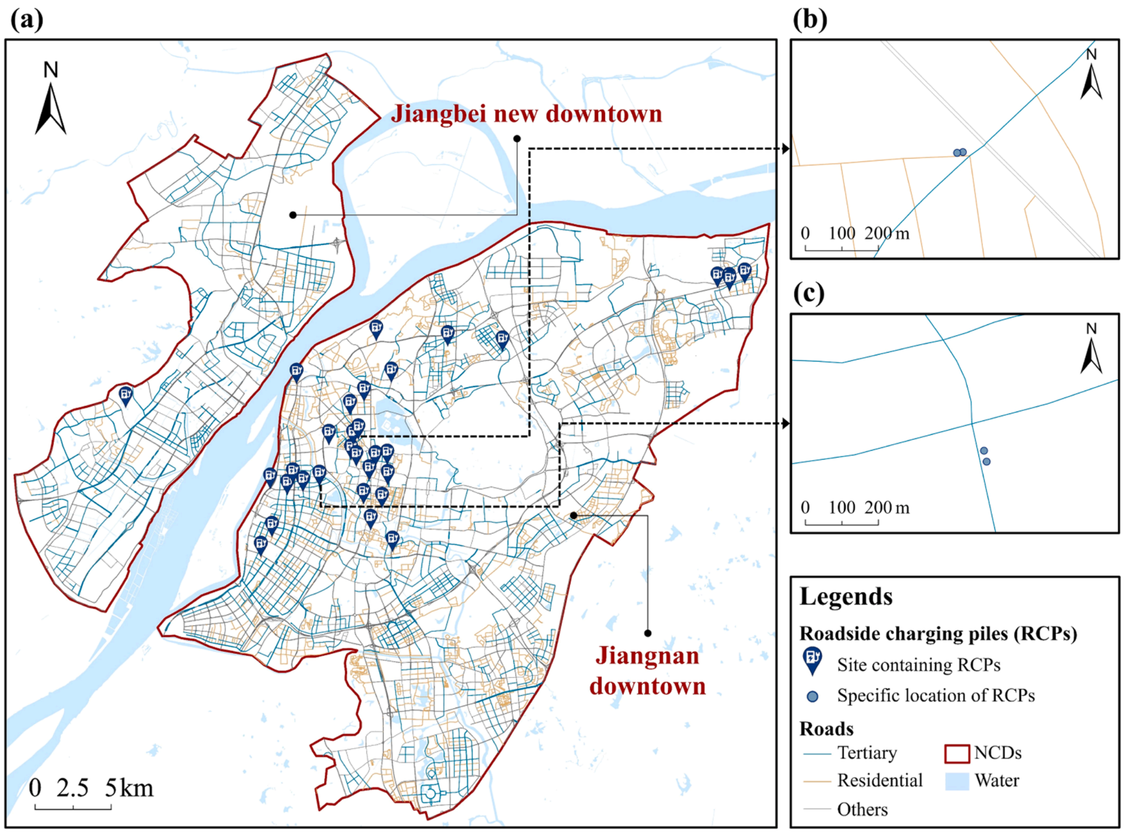


Fig. 9. Spatial distribution of RCPs in NCDs: (a) Distribution of charging piles in NCDs (b) Details of the first site marked in the figure (c) Details of the second site marked in the figure.

Table 4
Parameter settings in the BAU scenario.

Parameter	Value	Basis for Parameter Values
d_{max} (km)	0.9	This is consistent with the planning scheme "13th Five-Year Plan for Electric Vehicle Charging Infrastructure" issued by the Nanjing Municipal Transportation Bureau.
μ (EVs/ day)	4	Based on empirical EV charging patterns, private EV users typically require ≤5 h per charging session (Wang et al., 2021), enabling each RCP to service no fewer than 4 EVs per day.
k_{min} (EVs) k_{max} (EVs)	1200 1700	Following Nanjing's Implementation Plan for Large-Scale Equipment Renewal and Consumer Goods Replacement (2024–2027), which targets 5000 new public charging piles, we assume that RCPs will constitute 30 %–40 % of the total allocation targets through 2025–2030.

Table 5
Parameter settings in four scenarios.

Scenario	$d_{\max}$ (km)	μ (EVs/day)	$k_{\min}$ (EVs)	$k_{\max}$ (EVs)
BAU Scenario	0.9	4	1200	1700
EQ Scenario	1.0	4	1400	2200
EF Scenario	0.5	5	500	1200
BD Scenario	0.7	5	1400	1700

aging neighborhoods. Furthermore, more RCPs are allocated to Jiangbei new downtown to align with the Nanjing government's priority of developing Jiangbei new downtown. This balanced network avoids over-centralization, concurrently supporting SDG 7.1 and 7.3. Incorporating renewable energy into RCP operations could further align with SDG 7.2, contingent on implementation details.

These scenarios impose varying grid and investment demands. Nanjing is advised to align RCP strategies with developmental priorities by 2030. We recommend the BD scenario for its balanced approach: ensuring equitable access and promoting sustainable energy use. Implementation should prioritize sufficient coverage in high-density areas and new downtowns to advance both charging equity and sustainable urban growth.

4.3. Estimation results of roadside charging capacity

To estimate the roadside charging capacity, we formulate assumptions based on the current status of EVs adoption and RCPs deployment in NCDs, with parameter settings tailored to this specific context. Based on the roadside charging demand, the RCPs in NCDs are estimated to support a charging demand of approximately 301,537 kWh per day, which equates to 110.1 GWh per year, consisting of approximately in 86.4 GWh Jiangnan downtown and 23.7 GWh in Jiangbei new downtown.

Based on the four SDG 7-driven planning scenarios, the additional RCPs under the BAU, EQ, EF and BD scenarios are projected to support a potential annual charging capacity of approximately 85.8 GWh, 153.5 GWh, 103.2 GWh, and 148.3 GWh in the NCDs by 2030. Among these, 50.6 GWh, 79.8 GWh, 51.2 GWh and 68.0 GWh in Jiangnan downtown, and 35.2 GWh, 73.7 GWh, 52.0 GWh and 80.3 GWh in Jiangbei new downtown, respectively. The findings suggest that the BAU scenario prioritizes a greater provision of potential roadside charging capacity in Jiangnan downtown than in Jiangbei new downtown. If NCDs expands RCP deployment by 2030 based solely on existing policy and planning guidance, it will exacerbate service inadequacy in emerging development zones. The EQ scenario offers the highest available potential roadside charging capacity in Jiangbei new downtown and Jiangnan downtown, attributed to the largest number of newly added RCPs. While EF scenario maximizes the use of roadside charging resources, it also

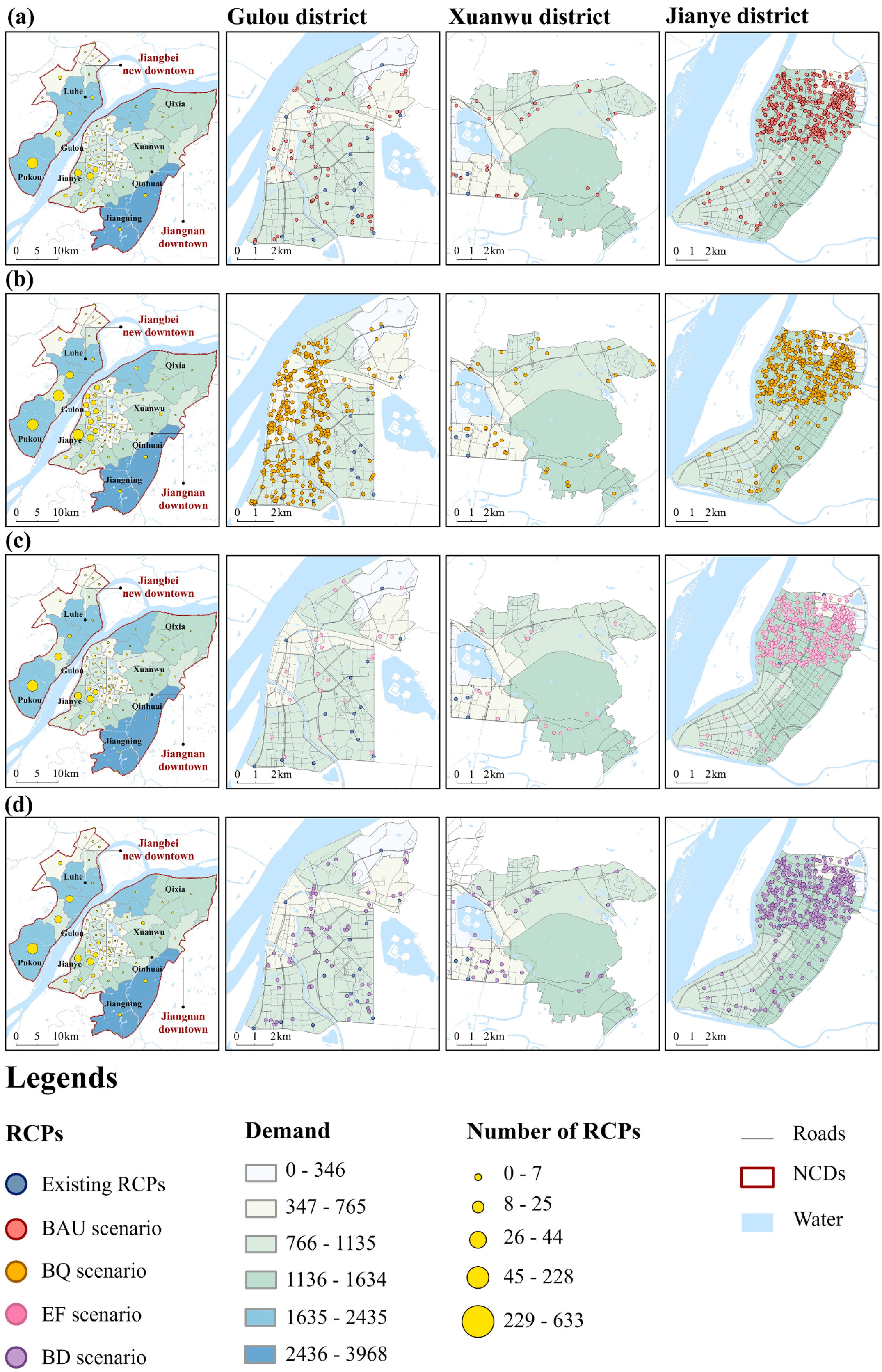


Fig. 10. Spatial distribution of existing and potential RCPs in NCDs under four scenarios: (a) BAU scenario (b) EQ scenario (c) EF scenario (d) BD scenario.

provides the lowest potential roadside charging capacity outside of the BAU scenario and faces significant challenges regarding equipment maintenance and technology upgrades. The BD scenario is optimal for the development of RCPs, as it provides greater potential roadside charging capacity in Jiangbei new downtown, ensuring alignment with planning guidelines and promoting the construction of RCPs in new urban areas.

5. Discussion

5.1. A cost-effective and accurate approach for detecting and locating urban RCPs

Different from recent studies that focus on small object detection and localization in the power sector (Xu et al., 2024), this research integrates street view imagery with geospatial knowledge-assisted detection algorithms and MLOS simulation to enhance the accuracy of urban RCPs localization and facilitate the precise calculation of their geographic coordinates. Our RCPs-YOLO model demonstrates an accuracy of 89.8 % and mAP of 77.4 % in detecting RCPs, revealing clustering in Nanjing's central urban zones attributed to higher population density and EV usage. This finding underscores the need for strategic urban planning to optimize RCP placement (Carra et al., 2022).

Our framework also accommodates various data sources, while initially developed with Baidu Street View, it can be transferred to other platforms like Google Street View, enhancing its global applicability. It provides precise geographic data for maintenance and supports sustainable urban development with the expansion of electric mobility.

5.2. Sensitivity analysis of SDG 7-driven planning model

To assess the robustness of the SDG 7-driven planning model, we conducted a sensitivity analysis on key parameters, including the maximum distance d_{max} and the daily EV charging capacity per RCP μ. This analysis evaluates how variations in these parameters affect the model's outputs, such as the spatial distribution of RCPs and overall accessibility.

We tested perturbations of ±10 % around the baseline values for d_{max} and μ in the BAU scenario (d_{max}=0.9 km, μ=4), while holding other parameters constant. For each perturbation, we recorded changes in the total number of allocated RCPs, the average travel distance to RCPs, and the unmet demand gap.

The results indicate that the model is relatively insensitive to small variations in d_{max} within the tested range, reinforcing its stability for urban planning applications. Conversely, when μ changes by 10 %, total RCPs and demand gap change by approximately 5–10 %, indicate that μ emerges as a key lever for optimizing demand coverage: increasing charging efficiency per RCP reduces demand gap with minimal impact on total RCPs or mean travel distance. This finding aligns with SDG 7 objectives by enabling more efficient use of existing infrastructure. Urban planners can thus prioritize capacity enhancements over extensive spatial adjustments when addressing demand shortfalls.

5.3. Policy implications for urban infrastructure management of sustainable development

Another contribution of this study is the proposal of an SDG 7-driven planning model for RCPs. It integrates urban planning with sustainability principles, ensuring that EV charging piles align with both local urban needs and SDG 7. The model emphasizes both charging accessibility and operational efficiency.

For NCDs, the BD scenario is recommended to prioritize the allocation of new RCPs toward new downtown development by 2030. Planned RCP installations could be implemented through phased deployment. This strategic focus is essential as these areas are projected to experience significant growth in electric vehicle adoption, necessitating robust charging infrastructure to support sustainable urban mobility. Our model indicates that under the BD scenario, this allocation would optimize both accessibility and efficiency, ensuring equitable distribution while maximizing usage rates. The planned installation of new RCPs can be implemented through a phased deployment strategy. Initially, high-demand zones identified in our geospatial analysis should be prioritized, such as commercial hubs and residential clusters with limited existing infrastructure. Subsequent phases would extend coverage to less densely populated areas, ensuring comprehensive city-wide access.

Currently, the integration of renewable energy sources into RCPs remains underdeveloped in Nanjing, largely due to insufficient policy support and infrastructure. Future efforts should prioritize incorporating renewable sources such as solar-powered charging piles (Huang et al., 2019) to advance SDG 7.2 alignment and reduce electricity grid load. Government subsidies for green infrastructure will be crucial to facilitate this transition. By providing financial incentives for the installation of solar panels on RCPs, policymakers can make renewable energy integration more economically feasible for operators. Additionally, such measures would support Nanjing's local sustainability objectives, including reducing carbon emissions and promoting clean energy, while contributing to global climate commitments.

5.4. Future applicability and limitations

This study offers a replicable framework for enhancing EV infrastructure that can be adopted in diverse urban contexts. The city-scale RCP street-view dataset reduces the need for manual annotation in other settings, thereby improving RCP detection and planning efficiency. It also supports advanced automation strategies, such as active or transfer learning, to minimize human intervention and enhance scalability. The SDG 7-driven planning model is designed for adaptability across diverse urban contexts through its flexible parametric structure. Parameters such as service radii and utilization rates can be tailored to local EV adoption patterns and charging behaviors. For instance, cities with high EV penetration may require smaller service radii to support denser charging networks.

The limitation of this study stems from the temporal and spatial constraints associated with street view imagery. The findings on RCP distribution in Nanjing rely on existing BSV images, which may be outdated; consequently, newly installed RCPs may not be captured in the dataset. Incomplete coverage on minor roads and occlusions from vehicles can also reduce detection accuracy (Campbell et al., 2019; Ma et al., 2025). Future implementations could address these issues by integrating iterative recapture technologies, such as backpack photogrammetric devices (e.g., Google Trekker) (Zhang et al., 2024), wearable cameras (Li et al., 2022b; Zhang et al., 2021) and the generation of street view images using satellite imagery (Qian et al., 2025), enabling annual updates to track RCP deployment and improve spatial-temporal completeness.

The SDG 7-driven planning model operates at a strategic level and thus does not directly incorporate the dynamics of electricity grid load. Our model proceeds on the assumption that impacts of electricity grid load at the selected sites can be mitigated through complementary strategies, such as using charging scheduling on regional clean energy power supply network management (Zhou et al., 2025), and using distributed generators to reduce negative impacts on the electricity grid (Aggarwal et al., 2024). Consequently, micro-level impacts of electricity grid load studies would be a valuable next step to enhance the model's applicability to real-world urban energy systems.

6. Conclusion

This study proposes a framework for locating and planning RCPs, aiming to estimate the potential roadside charging capacity. A case study was conducted in NCDs, where we identified and geolocated existing RCPs and evaluated potential allocation sites under SDG 7-

driven planning scenarios. This empirical application verified the feasibility and practicality of the proposed framework. The study revealed that RCPs in NCDs exhibit a clustering pattern, particularly with a concentration in Jiangnan downtown. Based on roadside charging demand, the RCPs can support up to 86.4 GWh in Jiangnan downtown and 23.7 GWh in Jiangbei new downtown. Guided by SDG 7, we proposed and evaluated four planning scenarios to project the spatial distribution and potential annual roadside charging capacity by 2030, with estimated capacities of 85.8 GWh, 153.5 GWh, 103.2 GWh, and 148.3 GWh, respectively. The results provide valuable insights for urban power management, public facility planning, and high-precision infrastructure mapping.

This study holds significant implications for urban management and smart city development. It recommends prioritizing BD scenarios, which emphasize the balance between accessibility and charging efficiency, and the prioritization of solar-powered RCPs to enhance renewable energy integration. The framework's adaptability, supported by its flexible parametric structure and compatibility with diverse data sources like Google Street View.

Future research should incorporate backpack photogrammetric devices, wearable cameras, and satellite imagery for updating street view imagery and integrate electricity grid load constraints alongside renewable energy sources. Such advancements would enhance the framework's precision, scalability, and alignment with SDG 7, thereby further supporting sustainable urban development and smart city initiatives globally.

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CRediT authorship contribution statement

Qin Huang: Writing – original draft, Methodology, Data curation, Conceptualization. **Teng Zhong:** Writing – original draft, Project administration, Methodology, Funding acquisition, Conceptualization. **Liangchen Zhou:** Writing – review & editing, Methodology. **Rui Zhu:** Writing – review & editing, Conceptualization. **Xiao Fu:** Writing – review & editing. **Changchang Zhou:** Writing – review & editing. **Min Chen:** Writing – review & editing, Supervision. **Guonian Lü:** 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.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2025.106789.

Data availability

Data will be made available on request.

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