Article:
Tian, X., Peng, F., McKechnie, J. et al. (2026) Sustainable battery recycling through spatial and technological alignment. Nature Sustainability. ISSN: 2398-9629

https://doi.org/10.1038/s41893-026-01851-6

nature sustainability

Analysis

https://doi.org/10.1038/s41893-026-01851-6

Sustainable battery recycling through spatial and technological alignment

Received: 24 June 2025

Accepted: 26 April 2026

Published online: 08 June 2026

Check for updates

Xi Tian (田西)[1,2,3,8], Fei Peng (彭菲)[2,8], Jon McKechnie[4], Amir F. N. Abdul-Manan[5], Yaobin Liu (刘耀彬)[6] & Fanran Meng (孟凡然)[7]

End-of-life (EOL) battery recycling is crucial for sustainable energy transition, yet existing systems often suffer from spatial, technological and policy mismatches that limit environmental benefits. Here we present a multi-scale analytical framework that integrates machine learning, life-cycle assessment and spatial integrated scenario modelling to evaluate the environmental footprint and resource recovery potential of battery recycling systems. This framework enables high-resolution projections of battery retirement trends, assessment of recycling technologies and optimization of supply–demand strategies. Using China as a case study, we analysed EOL battery flows across 364 cities and over 300 recycling projects involving 24 battery chemistries. The results reveal that, during 2020–2030, total EOL battery volumes amount to 16.67–19.99 Mt, with a northeast–southwest–northwest hotspot migration pattern. Interprovincial coordination can increase treatment capacity utilization by 67.12% but cannot eliminate spatial mismatches between EOL battery supply and available treatment capacity. Our optimization scenarios show that supply–demand planning could reduce emissions by up to 44% and increase lithium recovery by 53%. This work provides a scalable tool for designing low-carbon, high-efficiency battery recycling systems, contributing to the circular economy and energy transitions.

Electric vehicles (EVs) have emerged as an essential component of carbon neutrality strategies globally amid the energy transition[1,2]. The International Energy Agency projects that the global EV fleet will reach 230 million units by 2030[3]. China has maintained its position as the world's largest EV producer and consumer for a decade[4,5], with lithium-ion battery production capacity reaching 732.5 GWh[6], accounting for over 70% of global production. However, the industry faces a wave of battery retirements owing to capacity degradation (below 70–80% of initial capacity)[7]. The recovery of end-of-life (EOL) power batteries is crucial for mitigating supply risks associated with key materials[8], such as lithium, cobalt and nickel, for which China's import dependence exceeds 85%, 95% and 90%, respectively[9]. The chemical constituents of lithium-ion batteries are not readily degradable in natural environments and can contaminate drinking water and soils[10,11]. These spent batteries are inherently unstable and flammable, as exemplified by the 2022 explosion at Critical Mineral Recovery, one of the world's largest lithium-ion battery recycling facilities[12]. Therefore, battery recycling not only addresses resource scarcity but also serves as a critical pathway for achieving synergistic pollution reduction and carbon mitigation.

[1]Research Center for Central China Economic and Social Development, Nanchang University, Nanchang, Jiangxi Province, People's Republic of China. [2]School of Economics and Management, Nanchang University, Nanchang, Jiangxi Province, People's Republic of China. [3]Engineering Research Center of Watershed Carbon Neutralization, Ministry of Education, Nanchang University, Nanchang, Jiangxi Province, People's Republic of China. [4]Faculty of Engineering, University of Nottingham, Nottingham, UK. [5]Life Cycle Assessment (LCA) Group, Technology Strategy and Planning Department (TSPD), Saudi Aramco, Dhahran, Saudi Arabia. [6]Philosophy and Social Sciences Laboratory of Data Science in Finance and Economics, Ministry of Education, Jiangxi University of Finance and Economics, Nanchang, People's Republic of China. [7]School of Chemical, Materials and Biological Engineering, Faculty of Engineering, University of Sheffield, Sheffield, UK. [8]These authors contributed equally: Xi Tian, Fei Peng. e-mail: f.meng@sheffield.ac.uk

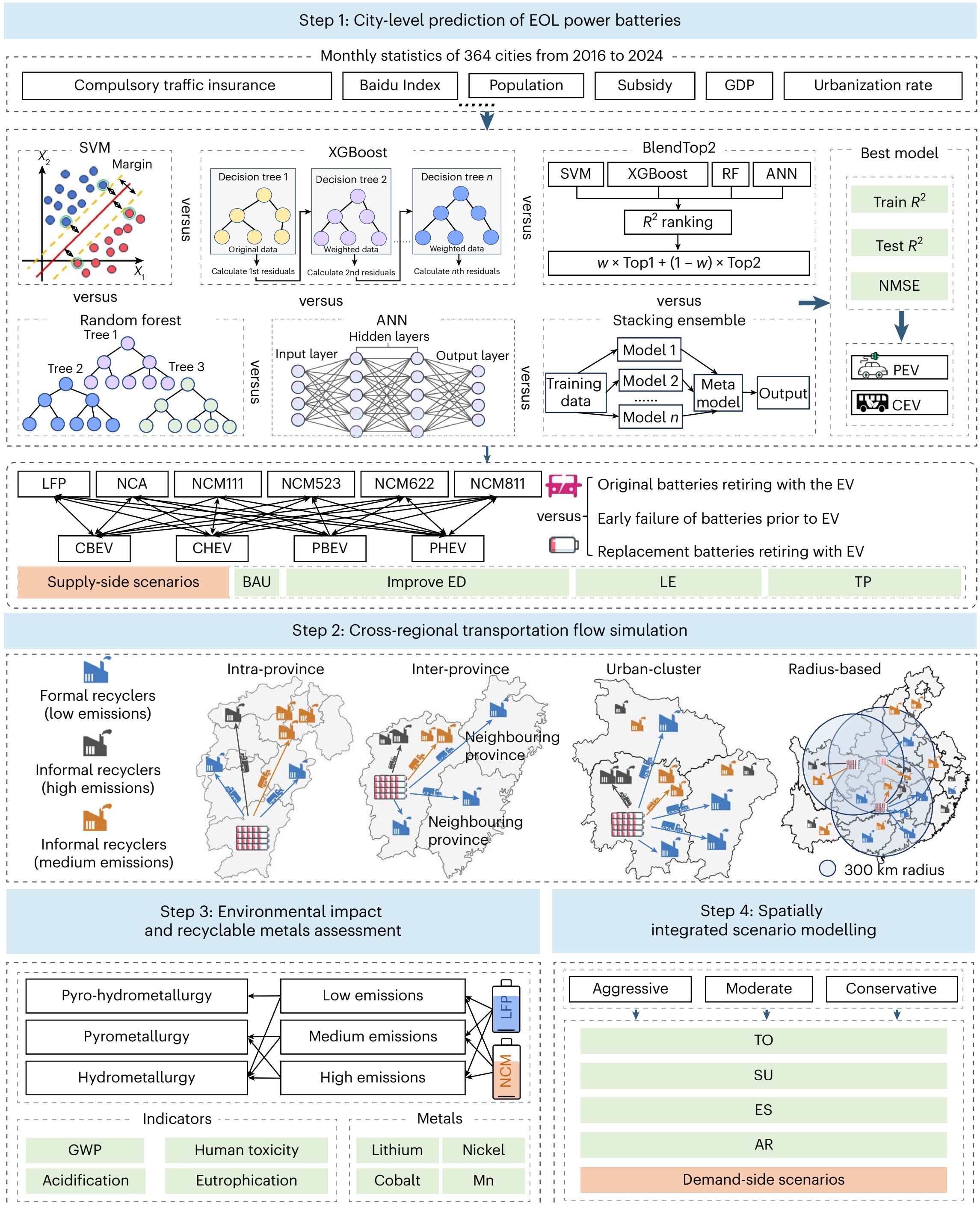


Fig. 1 | Spatial framework for sustainable battery recycling. EV sales data were sourced from Compulsory Traffic Accident Liability Insurance records. The BAU represents current conditions as of 2024. ANN, artificial neural network; CBEV, commercial battery EVs; CHEV, commercial plug-in hybrid EVs; Mn, manganese; PBEV, passenger battery EVs; PHEV, passenger plug-in hybrid EVs; NCA, nickel–cobalt–aluminium; RF, random forest; SVM, support vector machines; XGBoost, eXtreme Gradient Boosting. Basemaps from ref. 66; map data are based on standard map data approved under GS(2023)276773.

China's Ministry of Industry and Information Technology has officially recognized 156 qualified battery recycling enterprises, yet industry reports indicate over 50,000 active operators in this sector (https://www.qcc.com). Currently, only approximately 40% of EOL batteries are processed by qualified recycling enterprises[13], while the remainder flow into informal channels with limited technological capacity and insufficient environmental safeguards[14]. Informal recyclers typically consume larger amounts of acids, reductants and other chemicals, as well as higher levels of energy during processing[15,16]. This results in frequently overlooked upstream resource consumption and emission burdens[17,18]. Furthermore, according to the Greenhouse Gas Protocol[19] and ISO 14064[20], electricity- and heat-related burdens are directly proportional to the structure of the local grid and the associated fuel supply[21,22]. Thus, under identical energy consumption, provinces dominated by coal exhibit grid emission factors several times higher than those dominated by hydropower, leading to environmental outcomes that differ by orders of magnitude for the same recycling process[23]. Macro-scale management frameworks demonstrate limited adaptability to municipal-level dynamic characteristics. Achieving localized 'proximity-based recycling and disposal' of EOL power batteries[24] requires systematic consideration of regional disparities in industrial infrastructure, technological capacity and resource endowments. Consequently, granular regional analyses of recycling potential and environmental differentials become imperative.

Existing studies have employed the Stanford model[25], material flow analysis[26,27] and Weibull lifetime distribution models[25,28] to forecast EOL power battery volumes. However, these approaches often rely on a single type of dataset, such as historical sales[27], installed capacity[29] or average battery lifetime. Their spatial resolution is typically limited to national or provincial averages[30], overlooking heterogeneity at the city level. Moreover, their temporal resolution is restricted to annual increments, missing short-term fluctuations. As a result, these models are constrained in their ability to capture nonlinear systemic effects arising from the interaction of economic development, policy shifts, population structure and residents' attention. Accurate quantification of EOL power battery volumes and region-specific emission factors proves essential for reliable carbon emission inventories[11,31]. However, existing methodologies predominantly employ national-average values for project-specific emission accounting[32] or extrapolate single-process conditions to estimate nationwide carbon footprints[33]. Informal recycling enterprises demonstrate emission intensities several-fold higher than certified entities in China[18]. Previous studies have focused on industry leaders[32] or examined technological evolution in isolation, neglecting spatial disparities in technical capabilities and resource allocations[21], thereby systematically underestimating aggregate environmental burdens. Therefore, accurately quantifying pollution reduction potentials and informing region-specific governance strategies poses challenges that require granular analyses of heterogeneity in regional recycling-system configurations and variation in technological portfolios.

In response to these challenges, a multi-scale coupled framework is developed to integrate city-level battery retirement forecasting, cross-regional flow simulation, provincial life-cycle assessment (LCA) and spatially integrated scenario modelling (Fig. 1). Using EV insurance records from 364 Chinese cities (Supplementary Note 1), we project the retirement of 24 battery chemistries from 2020 to 2030 and map their spatial evolution. We then link alternative routing scenarios with a provincial database covering nearly 300 recycling projects, including technology portfolios, electricity mixes and treatment capacities. Overall, this framework shows how spatial and technological mismatches shape recycling performance, and helps identify optimized pathways towards lower-emission, higher-efficiency battery recycling systems.

Results

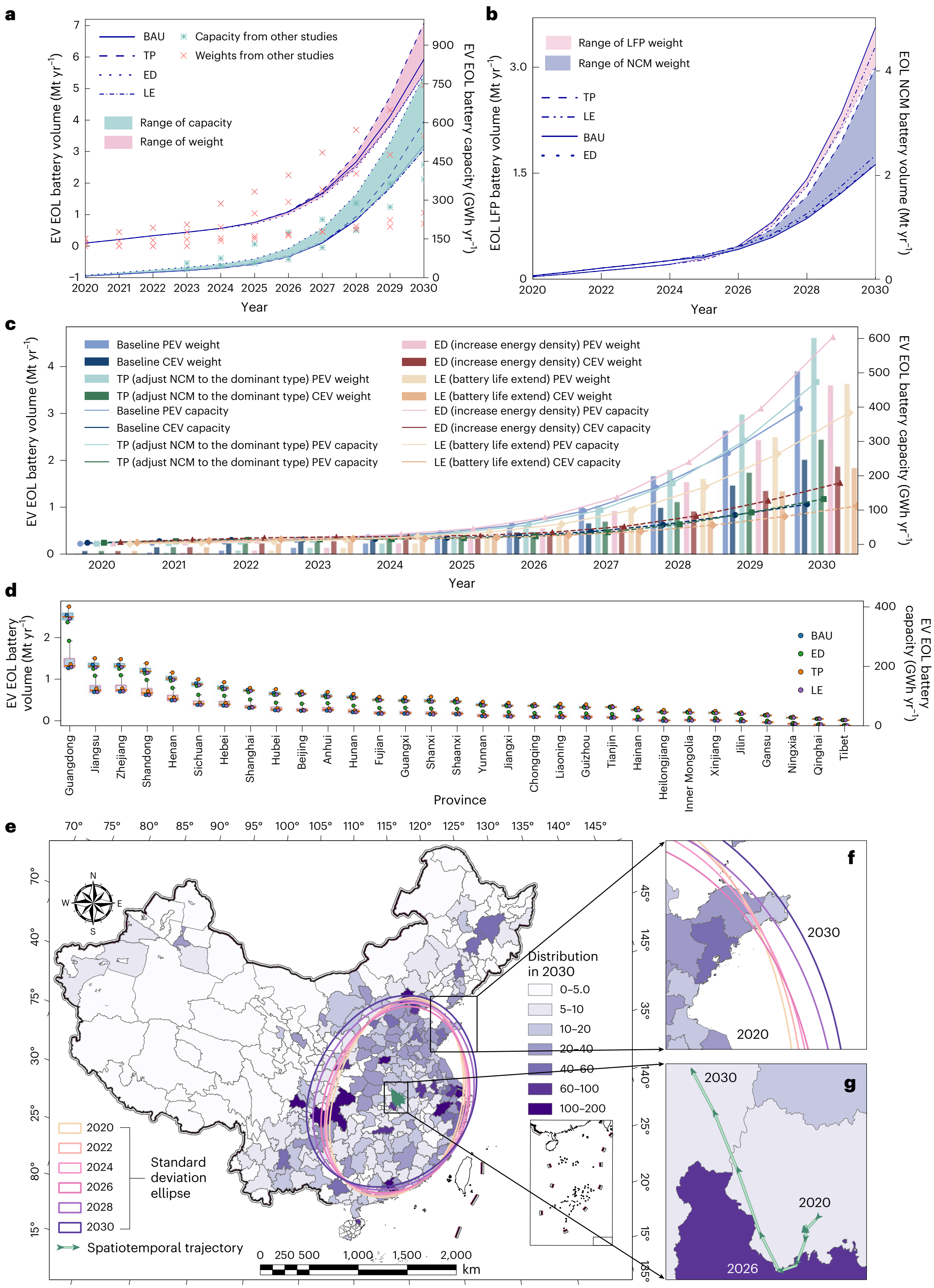
Spatiotemporal pattern of EOL batteries

A variety of cities are distinguished by a set of characteristics, including population size, gross domestic product (GDP), urbanization rate, local EV promotion subsidies and the Baidu search index for EVs. After embedding city-level features of passenger EVs (PEVs) and commercial EVs (CEVs) using principal component analysis, *k*-means clustering automatically determined the optimal number of clusters, resulting in three stable groups. The parameters of the optimal model for each cluster are shown in Supplementary Note 11. Based on the coefficient of determination (R^2) and normalized mean square error (NMSE) metrics of the optimal models, the extreme gradient boosting algorithm was found to be more suitable for predicting CEVs, whereas the artificial neural network model performed better in forecasting PEVs (Supplementary Table 5). Model predictions indicate that PEV sales are projected to reach a cumulative total of 155.93 million between 2025 and 2030, exhibiting a gradient diffusion pattern from eastern coastal regions to central and western areas (Supplementary Fig. 1). By contrast, the distribution of CEVs gradually evolved over time, exhibiting a pronounced disparity between the densely concentrated southeast and the sparsely populated northwest (Supplementary Fig. 2). Marked divergence is observed between these two distribution evolution trajectories.

We analysed the volume of EOL EV batteries across national, vehicle type, battery chemistry and regional dimensions. As illustrated in Fig. 2a–d, at the national level, EOL battery mass increased from 98,901 t in 2020 to a projected range of 5.48–7.07 Mt by 2030, with a compound annual growth rate of 50.59%. Over the period 2020–2030, the cumulative volume of EOL batteries is projected to reach 16.67–19.99 Mt. Retirement patterns exhibit phased characteristics: CEV batteries dominated retirements before 2024, while PEV retirements surged post-2024, accounting for 65.90% of total retired mass by 2030. This shift originated with the Chinese government's 2009 launch of the 'Ten Cities and One Thousand Vehicles' EV demonstration project[34], which covered public transit, taxis, government fleets, municipal services and postal logistics in major cities; it prioritized the deployment of electric commercial vehicles, whose higher utilization rates accelerated retirement. In battery chemistry terms, lithium iron phosphate (LFP) batteries remain dominant under the baseline scenario (BAU), comprising 60.10% of retired mass by 2030. If LFP installations fall to zero by 2030 and nickel–cobalt–manganese (NCM) batteries gradually become dominant (type proportion (TP) scenario, refers to the situation where nickel–cobalt–manganese (NCM) batteries gradually become dominant)), the retired volume of NCM batteries peaks at 4.04 Mt. In addition, using a stochastic capacity decay model for 24 battery types combined with a weighted retirement mass algorithm, EOL capacities were calculated across scenarios. Battery energy density enhancement (ED) yielded the highest EOL capacity (783.18 GWh by 2030), whereas battery lifespan extension (LE) reduced capacity to 498.56 GWh by delaying retirements, underscoring the pivotal role of technology in regulating resource metabolism.

As shown in Fig. 2e–g, EOL traction battery volumes are highly spatially aggregated. This clustering is associated with regional economic development levels and the distribution of the EV industry. For example, Guangdong Province accounted for the largest share of EOL power batteries during 2020–2030, at 14.19%, while its GDP ranked first nationwide in 2024 (Supplementary Table 2). In the three provinces

Fig. 2 | Predicted EOL power battery volumes in China and spatiotemporal distribution patterns of EOL power batteries from 2020 to 2030. **a**, Predicted EOL power battery volumes and capacity in China from 2020 to 2030, compared with predictions from other studies. **b**, Predicted EOL volumes of LFP and NCM batteries in China from 2020 to 2030. Shaded bands indicate the projected range across the four scenario pathways (BAU, ED, TP and LE) and do not represent statistical confidence intervals. **c**, EOL battery volumes for PEVs and CEVs under the BAU, ED, TP and LE scenarios, respectively. **d**, Province-level total EOL battery volumes and capacities for PEVs and CEVs during 2020–2030. For each province, the left box shows the distribution of total volume (Mt) across the BAU, ED, TP and LE scenarios, and the right box shows the corresponding distribution of battery capacity (GWh). Dots indicate individual scenario values (n = 4 scenarios per province), centre lines indicate medians, blue boxes indicate interquartile ranges for Mt, red boxes indicate interquartile ranges for GWh and whiskers indicate minimum and maximum values. **e**, Urban-level distribution of EOL power batteries in 2030. **f**, Standard deviation ellipse represents the spatial dispersion characteristics of EOL power batteries. The long half-axis of the ellipse represents the direction of the data distribution and the short half-axis represents the range of the data distribution. **g**, Geographic centroid migration of EOL batteries from 2020 to 2030. The green arrows denote gravity centres, while green lines illustrate the temporal trajectory of centroid movement. The arrowed path starts at the 2020 centroid and ends at the projected centroid for 2030, indicating the dynamic flow of EOL battery generation over the decade. Numerical values can be found in the Source Data for Fig. 2. Basemaps in **e**–**g** from ref. 66; map data are based on standard map data approved under GS(2023)276773.


a
EV EOL battery volume (Mt yr⁻¹)
EV EOL battery capacity (GWh yr⁻¹)
BAU
TP
ED
LE
Capacity from other studies
Weights from other studies
Range of capacity
Range of weight
Year
b
EOL LFP battery volume (Mt yr⁻¹)
EOL NCM battery volume (Mt yr⁻¹)
Range of LFP weight
Range of NCM weight
TP
LE
BAU
ED
Year
c
EV EOL battery volume (Mt yr⁻¹)
EV EOL battery capacity (GWh yr⁻¹)
Baseline PEV weight
Baseline CEV weight
TP (adjust NCM to the dominant type) PEV weight
TP (adjust NCM to the dominant type) CEV weight
Baseline PEV capacity
Baseline CEV capacity
TP (adjust NCM to the dominant type) PEV capacity
TP (adjust NCM to the dominant type) PEV capacity
ED (increase energy density) PEV weight
ED (increase energy density) CEV weight
LE (battery life extend) PEV weight
LE (battery life extend) CEV weight
ED (increase energy density) PEV capacity
ED (increase energy density) CEV capacity
LE (battery life extend) PEV capacity
LE (battery life extend) CEV capacity
Year
d
EV EOL battery volume (Mt yr⁻¹)
EV EOL battery capacity (GWh yr⁻¹)
BAU
ED
TP
LE
Guangdong
Jiangsu
Zhejiang
Shandong
Henan
Sichuan
Hebei
Shanghai
Hubei
Beijing
Anhui
Hunan
Fujian
Guangxi
Shanxi
Shaanxi
Yunnan
Jiangxi
Chongqing
Liaoning
Guizhou
Tianjin
Hainan
Heilongjiang
Inner Mongolia
Xinjiang
Jilin
Gansu
Ningxia
Qinghai
Tibet
Province
e
Distribution in 2030
0–5.0
5–10
10–20
20–40
40–60
60–100
100–200
2020
2022
2024
2026
2028
2030
Standard deviation ellipse
Spatiotemporal trajectory
0 250 500 1,000 1,500 2,000 km
f
2030
2020
g
2030
2020
2026

 https://doi.org/10.1038/s41893-026-01851-6

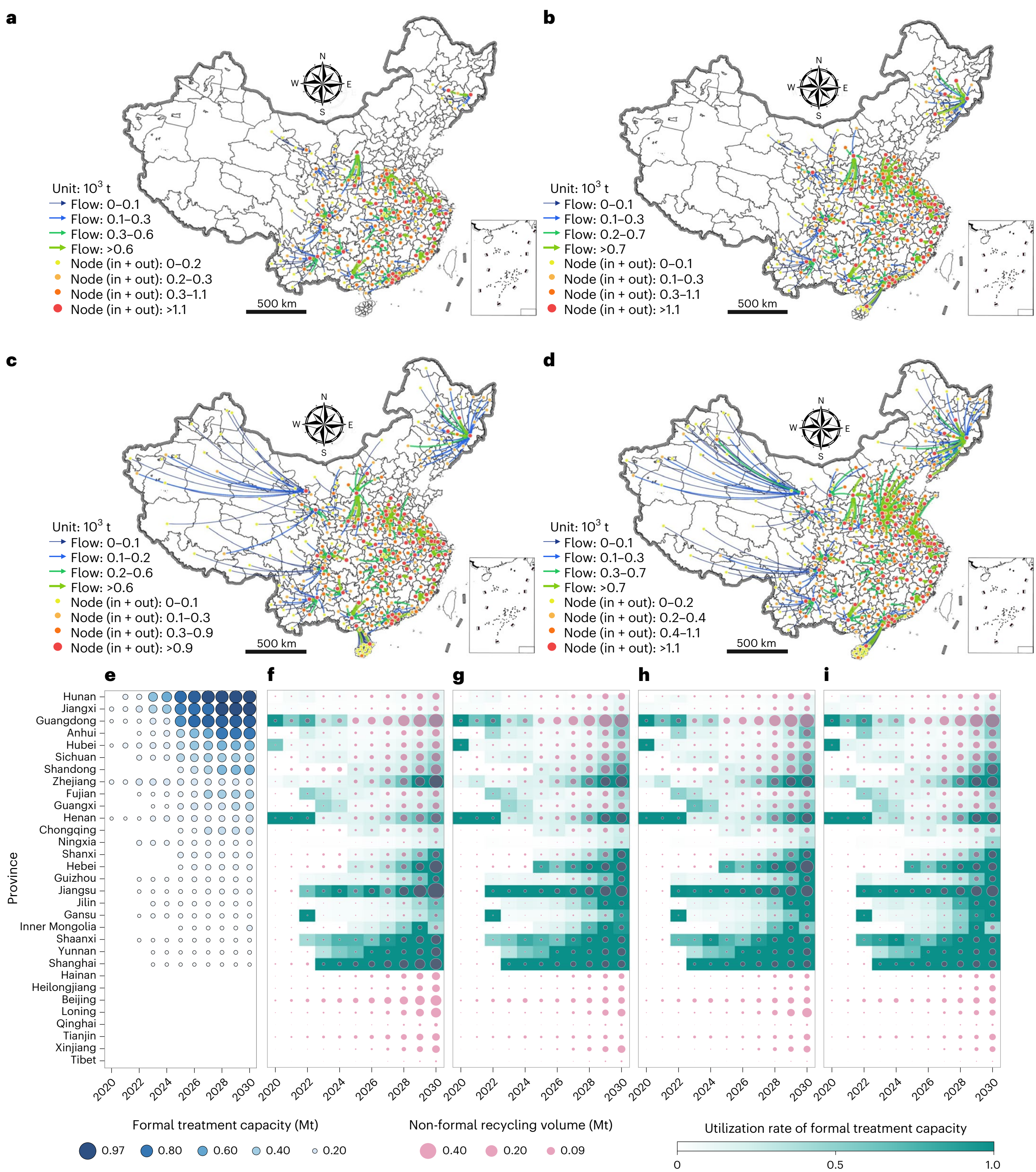


Fig. 3 | Flow diagram of cross-regional transport for EOL power batteries in China and distribution of treatment capacity among formal enterprises. **a**–**d**, Spatial flows of EOL power batteries under four scenarios: baseline (in-province recycling) (**a**), recycling within a fixed 300 km radius (**b**), recycling within urban agglomerations (**c**) and cross-border recycling to neighbouring provinces (**d**). Inset maps show the national map of China, including the South China Sea islands, for geographic reference. **e**, Provincial formal processing capacities from 2020 to 2030, with darker blue shading and larger bubbles indicating higher capacities. **f**–**i**, Capacity utilization rates and informal recycling volumes under the four scenarios defined in **a**–**d**, respectively. Darker green shading represents higher utilization rates, while larger pink bubbles indicate greater informal recycling volumes. Detailed results are provided in Source Data Fig. 3. Basemaps in **a**–**d** from ref. 66; map data are based on standard map data approved under GS(2023)276773.

following Guangdong in GDP ranking—Jiangsu, Shandong and Zhejiang—the volumes of EOL power batteries were also among the highest. The standard deviation ellipse indicates that the distribution of early EOL power batteries was more clustered, but with the expansion of EV and the expiration of battery lifespans, the distribution began to extend along a southeast–northwest axis. Spatial trajectory analysis via ArcGIS further reveals a distinct progression pattern in battery retirement distribution: initially from the northeast to the southwest, and beginning in 2026, shifting from the southeast to the northwest. This migration pattern implies that future recycling systems should not be planned solely around the current geography of battery manufacturing, but should anticipate the temporal relocation of EOL battery supply.

Cross-regional transportation and capacity distribution

This study analyses the spatiotemporal mismatch between battery formal treatment capacity allocation and retired battery distribution, along with its environmental impacts, using LCA based on data from about 300 battery recycling projects, provincial electricity consumption profiles and eight recycling technologies. Here formal treatment capacity refers to the treatment capacity of licensed facilities to handle EOL batteries through second-use and material-recovery pathways. Information on recycling projects was collected, including project initiation data, process-level energy consumption, technology types, equipment details, and the volumes and types of recovered materials. The licensed formal treatment capacity for EOL batteries increased from 0.13 Mt yr^{-1} in 2020 to 7.40 Mt yr^{-1} by 2030 (Fig. 3e). In line with the Ministry of Ecology and Environment's emphasis on encouraging local recycling and utilization of EOL power batteries[24], the BAU in this study assumes that retired batteries are recycled within the province of origin. However, in reality, numerous small and micro enterprises are also competing for discarded batteries.

In the presence of competition from informal collectors, spatial coordination is pivotal to raising the utilization of licensed treatment capacity. Under the baseline, where interprovincial routing is restricted, national-average capacity utilization in 2024 was only 39.3%, reflecting a dual constraint of distance and limited receiving options. This manifests heterogeneously—provinces such as Guangdong host substantial licensed capacity yet face intense competition from informal operators, while Zhejiang and Jiangsu exhibit high EOL battery generation but comparatively sparse licensed recycling enterprises, producing the combination of elevated formal capacity utilization and persistently high informal recovery. Allowing cross-regional transport mitigates these spatial mismatches (Fig. 3f–i). Under neighbouring-province coordination (Fig. 3d), the 2024 national-average utilization rises to 65.68%—an absolute gain of 26.38% over baseline (a 67.12% relative increase). A city-cluster scheme (Fig. 3c), leveraging networked consolidation within metropolitan systems, achieves 58.22%, materially above baseline yet below neighbouring-province performance. By contrast, a simple 300 km radius (Fig. 3b) constraint expands reach but remains less targeted to structural spatial imbalances than province-based or cluster-based coordination. However, in provinces such as Jiangxi, Hunan and Hubei, volumes of EOL power batteries are smaller, whereas formal treatment capacity is substantial; even with cross-provincial transport, capacity utilization remains well below 50%. In addition, transportation-related emissions are estimated to account for less than 1% of process-wide emissions from battery recycling. These results indicate that the main constraint on system performance is not transport itself, but the spatial mismatch between licensed capacity and waste generation, suggesting that coordinated routing can be environmentally justified when recycling burdens dominate transport emissions.

Provincial environmental effects and metal recovery

Fig. 4a–i illustrates the environmental impacts per recycled battery unit based on 2023 electricity consumption patterns. The disparity in provincial electricity structures directly causes variations in environmental footprints under identical technological conditions. Environmental impact assessments for recycling 1 t of EOL power batteries reveal Inner Mongolia, Heilongjiang, Jilin, Shanxi and Hainan as the top five provinces with the highest global warming potential (GWP). These findings highlight the importance of optimizing recycling facility siting strategies and accelerating grid decarbonization to mitigate regional environmental burdens. For example, the GWP generated by low-emission hydrometallurgical recycling of 1 t of LFP batteries in Shanxi Province is equivalent to that from recycling 3.35 t of LFP batteries via the same process in Hubei Province. The maximum provincial divergence in GWP for low-emission hydrometallurgical recycling of 1 t of NCM batteries exceeds 3.61 tCO_2e. Furthermore, GWP from small informal enterprises is 2.12–8.40 times higher than that from certified hydrometallurgical processes, and 3–9 times greater than pyro-hydrometallurgy technology, whereas the human toxicity potential (HTP) is more than 15 times higher. These disparities underscore the urgency of phasing out outdated capacities and advancing standardized management practices. However, for low-emission hydrometallurgical NCM recovery processes, their lower GWP is accompanied by a higher acidification potential (AP).

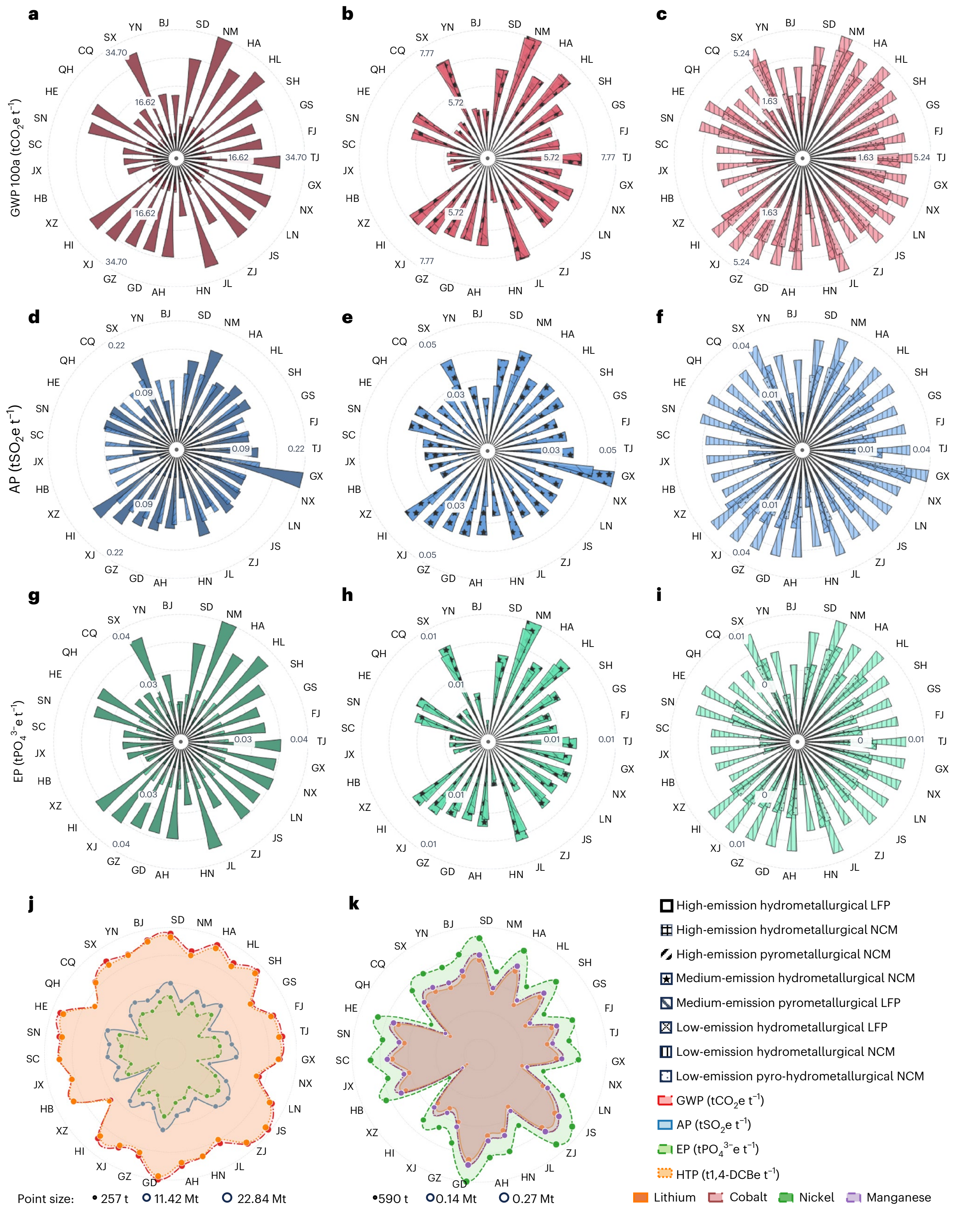
The provincial proportions of recycling technologies were quantified using battery production capacity data and enterprise-type distributions (Supplementary Notes 14 and 18). As shown in Fig. 4j,k, the five provinces with the highest total recycling-related emissions during 2020–2030 are Guangdong, Jiangsu, Shandong, Shanghai and Zhejiang. Although GDP in these provinces is among the highest nationwide, deficiencies in standardized recycling technologies among formal-sector enterprises are observed in Jiangsu and Shandong, whereas Shanghai's higher emissions are associated with its coal-dominated electricity mix. The top five lithium recovery provinces, Guangdong, Zhejiang, Shandong, Jiangsu and Henan, collectively contribute 42.6% of national lithium recovery volumes. High volumes of EOL power batteries are also generated in these provinces. Notably, these five most polluting provinces also account for 40.83% of lithium recovery output, indicating that China's EOL power battery recycling industry remains dependent on inefficient recycling practices characterized by numerous small, low-tech operations.

China's power battery recycling industry exhibits regional disparities, with provinces facing distinct challenges in capacity matching, energy structure cleanliness and technological advancement. This under-utilization is not uniform across provinces: Guangdong has a high concentration of licensed recycling capacity but faces intense informal competition at the point of collection; Zhejiang and Jiangsu generate large EOL volumes yet host comparatively sparse licensed projects, resulting in a combination of localized capacity pressure and

Fig. 4 | Environmental impacts and metal recovery from China's power battery recycling industry by province. a–**i**, Provincial GWP (tCO_2e) (**a**,**b**,**c**), AP (tSO_2e) (**d**,**e**,**f**) and EP ($tPO_4^{3-}e$) (**g**,**h**,**i**) per 1 t of lithium-ion batteries recycled using high-emission (**a**,**d**,**g**), low-emission (**b**,**e**,**g**) and medium-emission (**c**,**f**,**i**) processes. **j**, Provincial total emissions for GWP ($MtCO_2e$), AP ($MtSO_2e$), HTP (Mt1,4-DCBe) and EP ($MtPO_4^{3-}e$) from 2020 to 2030. **k**, Provincial metal recovery volumes (t) for lithium, cobalt, nickel and manganese from 2020 to 2030. The concentric scale labels indicate the magnitude of each environmental indicator. Values are log-transformed and represented by radial lengths, uniformly scaled to one-thousandth of their original values. Labels are shown only on the outer and middle rings. Results for environmental impact indicators are provided in Source Data Fig. 4. AH, Anhui; BJ, Beijing; CQ, Chongqing; FJ, Fujian; GD, Guangdong; GS, Gansu; GX, Guangxi; GZ, Guizhou; HA, Henan; HB, Hubei; HE, Hebei; HI, Hainan; HL, Heilongjiang; HN, Hunan; JL, Jilin; JS, Jiangsu; JX, Jiangxi; LN, Liaoning; NM, Inner Mongolia; NX, Ningxia; QH, Qinghai; SC, Sichuan; SD, Shandong; SH, Shanghai; SN, Shaanxi; SX, Shanxi; TJ, Tianjin; XJ, Xinjiang; XZ, Xizang; YN, Yunnan; ZJ, Zhejiang.

https://doi.org/10.1038/s41893-026-01851-6

elevated informal recovery. Interior provinces Jiangxi, Anhui, Hunan and Sichuan are characterized by relatively small city-level volumes of EOL power batteries but a concentration of formal-sector treatment capacity. Consequently, a pronounced disparity emerges between available resources and inflows from neighbouring cities, resulting in under-utilized facilities while other provinces encounter shortages. Regions with cleaner electricity structures, such as Yunnan, Sichuan and Qinghai, demonstrate lower emissions, while northern provinces like Inner Mongolia, Shanxi and Jilin, heavily reliant on coal-fired power (>70%), maintain high carbon intensities of 3.30 $tCO_2e\ t^{-1}$ battery, even with low-emission technologies, urgently requiring clean energy transitions. Technologically, low-emission hydrometallurgical processes



https://doi.org/10.1038/s41893-026-01851-6

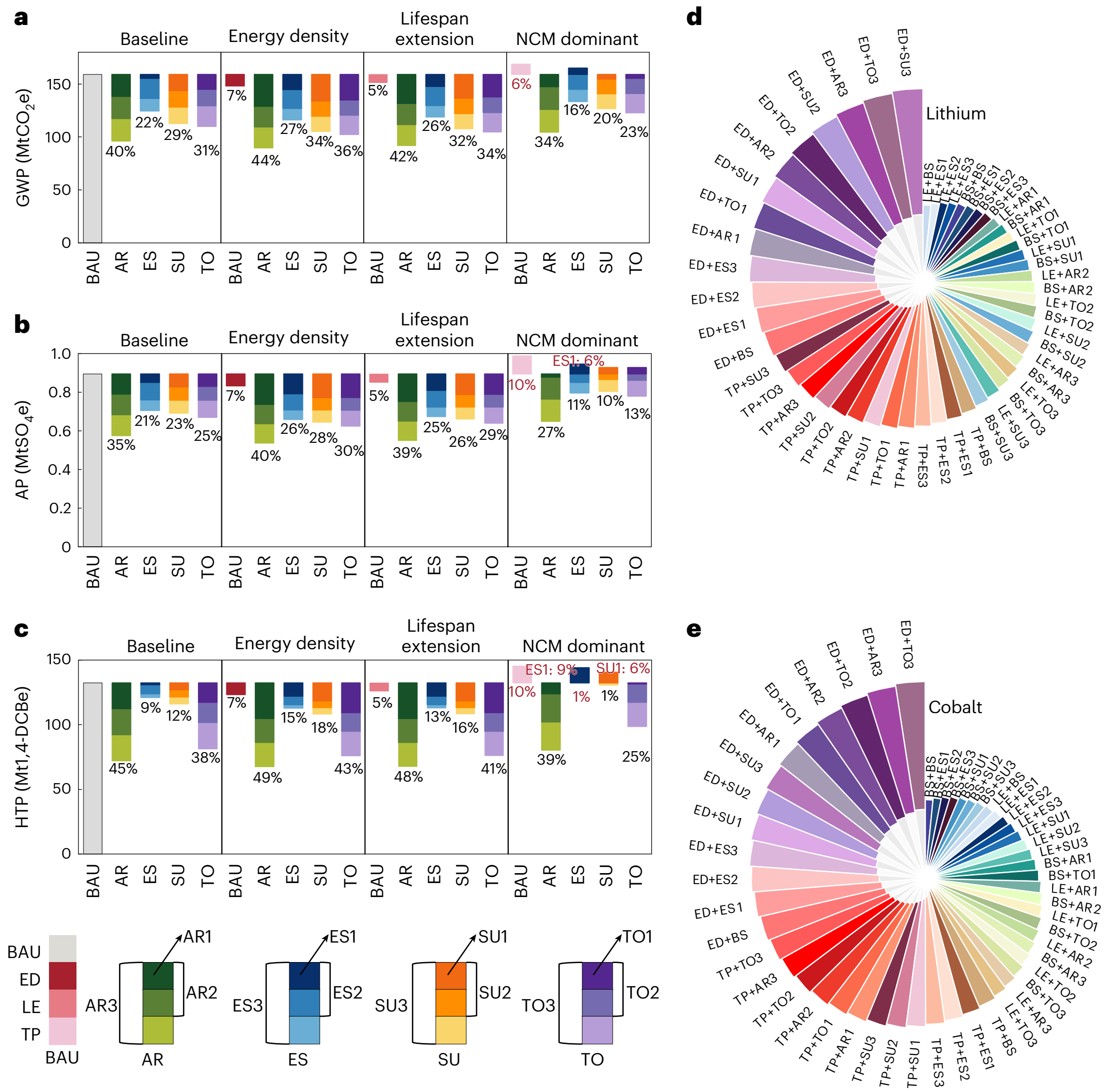


Fig. 5 | Potential for pollution reduction and metal recovery from 2020 to 2030 under 52 scenarios considering battery supply and recycling industry demand. a, Impact of 52 scenarios on GWP ($MtCO_2e$). **b**, Impact of 52 scenarios on AP ($MtSO_4e$). **c**, Impact of 52 scenarios on HTP (Mt1,4-DCBe). Black text denotes the proportion of emission reductions in aggressive scenarios, whereas red text indicates the proportion of emission increases. **d**,**e**, Recoverable volumes of lithium (**d**) and cobalt (**e**) for the 52 scenarios (Mt). The numerals 1, 2 and 3 are used to denote the conservative, moderate and aggressive scenarios, respectively. Other environmental impact and metals recovery results can be found in Source Data Fig. 5.

dominate (>50%) in Jiangxi, Hunan and Ningxia, but face high costs for acid wastewater treatment. Conversely, Shaanxi, Hebei, Tianjin and remote areas still predominantly use high-emission methods (>60%) and formal recycling rates below 50%.

Future waste, emissions and metal recovery

A scenario-based framework was formulated across supply–demand dimensions to analyse 52 scenarios (Extended Data Table 1), aggressive, moderate or conservative levels of technological optimization (TO), energy structure adjustment (ES), enhanced authorized recycling (AR) and secondary utilization (SU) under evolving battery chemistries, quantifying their pollution–carbon reduction and resource recovery implications. Under baseline conditions, cumulative national environmental burdens for 2020–2030 were quantified as 158.97 $MtCO_2e$ for GWP, 132.32 Mt 1,4-dichlorobenzene-equivalent (DCBe) for HTP, 0.89 $MtSO_2e$ for AP and 0.24 $MtPO_4^{3-}e$ for eutrophication potential (EP). In addition, the recoverable metal quantities of the projects were 0.13 Mt of lithium, 0.17 Mt of cobalt, 0.43 Mt of nickel and 0.17 Mt of manganese. In 2030, environmental impacts and metal recovery volumes accounted for more than 30% of the 2020–2030 cumulative totals.

As shown in Fig. 5a–c, the supply-side scenario dominated by NCM batteries (TP) exhibits the most substantial environmental impacts; per-unit burdens (GWP, AP, EP, HTP) exceed the baseline by 6%, 10%, 8% and 10%, with corresponding cumulative burdens of 168.67 $MtCO_2e$, 0.98 $MtSO_2e$, 0.26 $MtPO_4^{3-}e$ and 145.36 Mt1,4-DCBe. The results indicate that, when NCM batteries dominate vehicle installations, the system-wide environmental benefits of recycling are diminished. As shown in Fig. 5d,e, the combined ED and TO achieves maximum cobalt, nickel and manganese recovery at 0.26 Mt, 0.65 Mt and 0.26 Mt, respectively. The combined ED and increased SU yields the highest lithium recovery at 0.21 Mt. LE scenarios maintain lower environmental impacts but concurrently yield the lowest metal recovery volumes.

Under the demand-side scenario, the greatest reduction in GWP is achieved by directing batteries to AR, followed by recycling technology optimization, broader adoption of SU and, lastly, ES. The combined ED and a 60% increase in the formal recycling rate (ED + AR3) achieves reductions of 44% in GWP, 40% in AP, 47% in EP and 49% in HTP.

 https://doi.org/10.1038/s41893-026-01851-6

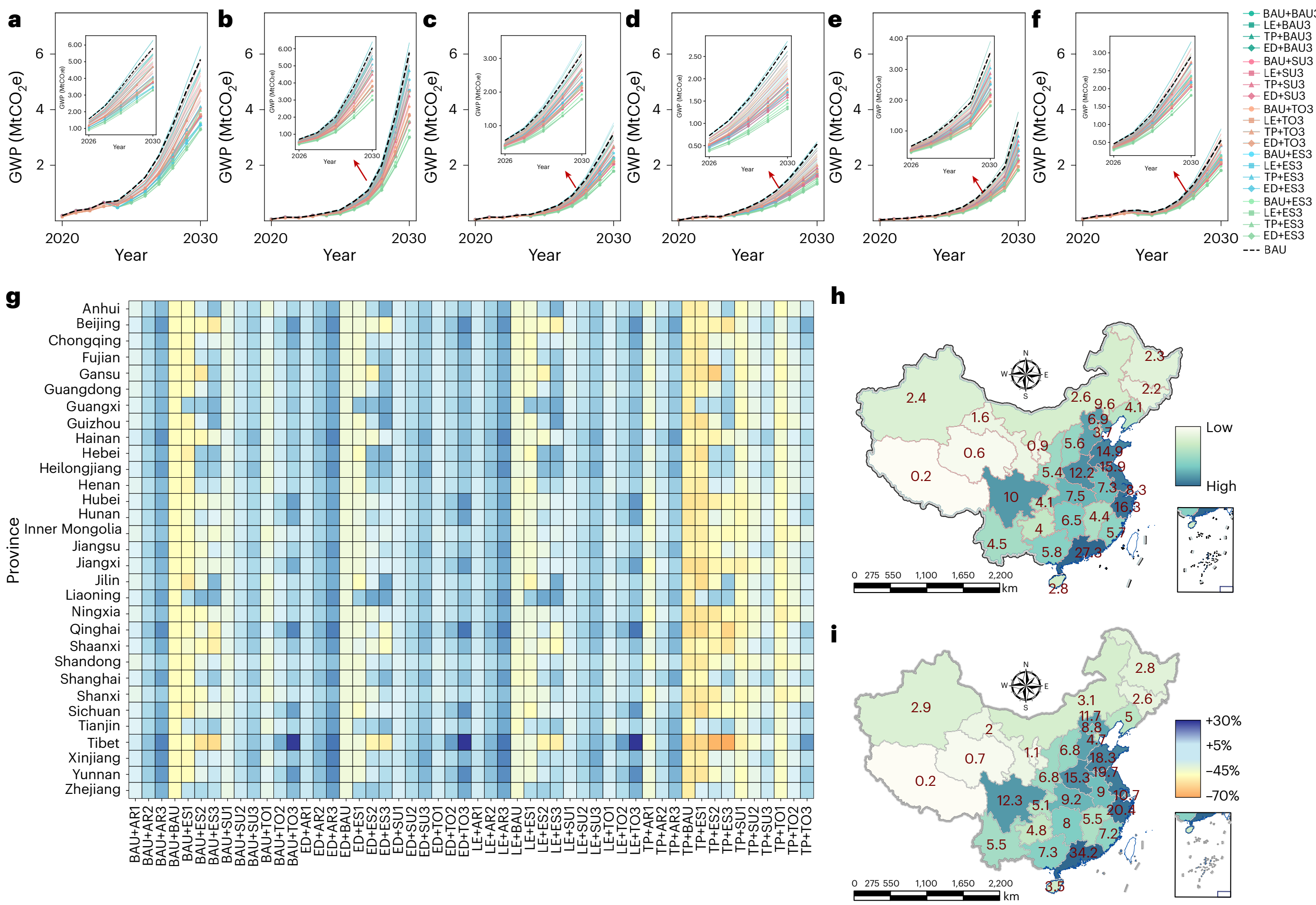


Fig. 6 | Pollution reduction, carbon mitigation potential and metal recovery across Chinese provinces under 52 scenarios. **a**–**f**, The six provinces (Guangdong (**a**), Jiangsu (**b**), Henan (**c**), Shanghai (**d**), Zhejiang (**e**), Shandong (**f**)) with the largest absolute reductions in GWP across 52 scenarios. Provincial emissions are specified as annual values for each year from 2020 to 2030, rather than cumulative totals. The inset plots highlight scenario-based emission reductions in cities from 2026 to 2030. Therefore, the *y*-axis scale adjusts according to each city's emission values. **g**, Percentage reduction in GWP in the 31 provinces of mainland China under the integrated scenarios compared with the BAU. **h**, Provincial recoverable lithium, 2020–2030 (10^3 t). **i**, Provincial recoverable cobalt, 2020–2030 (10^3 t). Darker map shading denotes larger recoverable metal volumes. Inset maps show the national map of China, including the South China Sea islands, for geographic reference. The numerals 1, 2 and 3 are used to denote the conservative, moderate and aggressive scenarios, respectively. Detailed environmental impact and metal recovery data are provided in Source Data Fig. 6. Basemaps in **h** and **i** from ref. 66; map data are based on standard map data approved under GS(2023)276773.

The supply-side LE scenario with 60% market-end technological advancement (LE + TO3) limits GWP to 34% of the baseline upper bound and reduces HTP by 41% relative to the baseline. Here TO3 denotes the most ambitious process-improvement pathway, in which energy use, reagent consumption and metal recovery rates are improved towards their thermodynamic minima. Across the energy-mix pathway, from a conventional structure (ES1) to a 2.0-compliant sustainable development pathway (ES2) and to a 1.5 °C-compliant pathway (ES3), GWP reductions range from 2.30% to 27% relative to the baseline, indicating that power-system decarbonization alone delivers limited mitigation in this context. At a SU rate of 0.60, GWP reductions range from 20% to 34%. SU is functionally equivalent, in material terms, to directing the lithium content of LFP batteries into new service applications, increasing lithium recovery by 55% (0.07 Mt) relative to the baseline.

As shown in Fig. 6a–g, regional pollution and carbon reduction strategies reveal spatial heterogeneity. For provinces such as Hubei, Hunan, Jiangxi and Chongqing, where formal-sector treatment capacity is concentrated, the largest reductions in GWP are achieved under TO (TO3), with an average reduction of 47%. For Guizhou and Jilin, which have coal-dominated power mixes, ES is most effective, with GWP reduced by 43%. For Anhui, Fujian, Zhejiang, Liaoning and several more remote provinces, the greatest mitigation effect is obtained by increasing the throughput of authorized recyclers. For Beijing, Hainan and Tibet, increasing the throughput of authorized recyclers raises lithium recovery by more than 58% and increases cobalt, nickel and manganese recovery by up to 58%. For Guangdong, Guangxi, Inner Mongolia, Shandong and Shanxi, cobalt, nickel and manganese recovery are increased, on average, by 53% through upgrades to recycling-process technology. The results represent the maximum benefits attainable under ideal implementation conditions, and their interpretation should account for the underlying assumptions.

Given the pronounced provincial differences in electricity structure and recycling performance, we further examined how simplifying these dimensions would affect the estimated emissions. To do so, we compared the BAU used in this study with two simplified cases that remove one source of heterogeneity at a time. A scenario that excludes provincial heterogeneity in electricity mixes, by adopting the national-average electricity dataset from ecoinvent 3.9.1, leads to an overestimation of total GWP by approximately 80%. By contrast, a scenario that excludes technological heterogeneity in recycling processes results in an underestimation of emissions by 66.08%. Together, these results show that both spatial and technological resolution are crucial for robust emission assessment. The provincial-level results for the three scenarios are reported in Supplementary Table 23, with a visual comparison provided in Supplementary Fig. 9.

Discussion

This study identifies three systemic challenges in China's power battery recycling sector: (1) a spatial mismatch between provincial treatment capacity and the distribution of retired batteries, which is exacerbated by competition between formal and informal recyclers; (2) spatially heterogeneous environmental burdens, as identical recycling processes generate several-fold differences in emissions across provinces due to divergent electricity mixes; and (3) technological-portfolio misalignment, as provincial reliance on different tiers of hydrometallurgical and pyrometallurgical routes introduces distinct constraints. For the relevant research community[25,35,36], the main contribution of our framework is that it links city-level retirement forecasting, cross-regional routing, provincial LCA and integrated scenario analysis within a single spatially explicit framework, thereby enabling a more policy-relevant assessment of where and how recycling should occur.

Notably, the observed migration of EOL battery hotspots, initially from the northeast to the southwest, and then shifting from the southeast to the northwest, highlights systemic mismatches between planned battery resource utilization capacity and projected supply. This study characterizes the transport dynamics under competition from informal recyclers. Within-province recycling leaves many formal facilities under-utilized, whereas in provinces with high retirement volumes, informal channels capture a larger share. Interprovincial coordination mitigates but does not eliminate these mismatches, particularly where formal capacity is overly concentrated and large relative to local inflows. To secure a stable supply of waste materials, some recycling facilities have been sited adjacent to battery manufacturing lines to collect and process production scrap. This practice supported the utilization of Chinese recycling facilities in the early stage[37]. However, with the impending large-scale retirement of traction batteries, the sector's focus is shifting towards the closed-loop recycling of EOL batteries. Transport-related emissions are less than 1% relative to processing, indicating that, under China's current geographic pattern, the environmental cost of interprovincial reallocation is minimal[38]. Therefore, the overall net benefit depends largely on whether high-emission processes and carbon-intensive regional electricity grids are effectively displaced.

The findings align with literature emphasizing spatial heterogeneity in recycling efficiencies[18,25], and are of the same order of magnitude as estimates based on a national-average electricity mix[10,39] (Supplementary Table 31). Comparisons presented in Supplementary Table 23 show that assuming a national-average electricity mix obscures substantial interprovincial variation in grid carbon intensity, while neglecting process heterogeneity overlooks differences in energy use, recovery efficiency and operational practices. These biases are sufficiently large to affect not only the absolute magnitude of environmental impacts but also the relative ranking of regions[40]. Together, these results underscore the need for high-resolution, spatially explicit and technology-resolved inventory data[41]. This work highlights the importance of regionally differentiated LCA frameworks, particularly in large and heterogeneous economies, where spatial and technological variability fundamentally shapes environmental outcomes. Therefore, province-level intervention priorities cannot be determined by recycling volume alone, but must also account for local grid carbon intensity and the composition of regional process portfolios.

Based on these patterns, we derive the following regionally differentiated strategy framework that can also be interpreted as a general typology of intervention priorities for heterogeneous recycling systems: (1) pre-emptive infrastructure deployment in emerging retirement hotspots to match projected growth in EOL batteries, as illustrated by the Yangtze River Midstream and Chengdu–Chongqing clusters; (2) in manufacturing-oriented regions with high retirement volumes and intense informal competition, illustrated here by parts of coastal China, prioritize formal-sector routing, enable cross-regional matching and procure renewable electricity to reduce unit environmental burdens; (3) in regions with high formal capacity but relatively low local retirement volumes, such as several central provinces, developing consolidation hubs and introducing process upgrades to absorb supplementary inflows; (4) in coal-intensive regions, link any new formal-sector capacity expansions to low-carbon electricity until reliable access to clean power is secured, discourage new energy-intensive pyrometallurgical stages and focus on the dismantling and transfer of intermediate products to certified refiners; and (5) strengthen formalization mechanisms by enforcing registration, penalties and incentives to integrate informal recyclers into regulated systems, making technical compliance a prerequisite.

Although China serves as the empirical case, the analytical logic is transferable to other rapidly electrifying economies and to emerging recycling chains characterized by spatially uneven waste generation, heterogeneous treatment technologies and differentiated electricity systems. Under such conditions, integrating high-resolution retirement forecasting with routing simulation and localized environmental assessment can provide a robust basis for siting decisions, technology upgrading and differentiated policy design. Through strategic planning, innovation and stringent governance, China can pioneer a globally leading, environmentally sustainable recycling system, accelerating progress towards circular economy and carbon neutrality goals.

Owing to data constraints, this study has three key limitations: (1) the data from informal recyclers are represented using the highest-emission hydrometallurgical and pyrometallurgical processes, as precise process-level data are unavailable; (2) this study assumes no imports of overseas spent batteries. Given that Chinese recycling enterprises currently process primarily domestically retired batteries and that cross-border transportation of waste batteries is restricted by regulation, this assumption is considered reasonable for the study period. However, if imports of waste batteries increase in the future, they should be incorporated into the model; and (3) in the simulated cross-regional transport scenarios, only transport distance and associated emissions are considered, while the economic costs of the long-distance shipment of EOL batteries are not evaluated. Future work should incorporate economic feasibility constraints on interprovincial transportation.

Methods

This study develops a multi-scale analytical framework to evaluate the environmental impacts and resource recovery potential of battery recycling systems. The framework consists of four linked components. First, city-level retirement of EOL batteries is forecast from 2020 to 2030 using machine learning based on EV insurance records and urban socio-economic indicators. Second, cross-regional battery flows are simulated under alternative routing rules to assess how spatial mismatch between retirement hotspots and licensed treatment capacity shapes formal recycling pathways. Third, a provincial LCA database covering nearly 300 recycling projects is constructed to capture regional technology portfolios, electricity mixes and treatment capacities. Fourth, these components are integrated into scenario modelling to evaluate how spatial allocation, technological upgrading and market evolution jointly affect environmental burdens and metal recovery.

City-level prediction of EOL batteries

To address the challenge of predicting battery retirements with limited historical data, we constructed a high-resolution forecasting framework that integrates machine learning with multifactorial urban characteristics. Our approach considers spatial heterogeneity by clustering cities with similar socio-economic and policy conditions, thereby improving predictive robustness for small samples.

First, we compile monthly datasets encompassing PEV and CEV insurance registrations across 364 Chinese cities, alongside five categories of urban indicators: (1) population size and GDP to capture market scale; (2) urbanization rates to reflect demographic dynamics; (3) local subsidies to account for policy incentives; and (4) Baidu Search Index to represent consumer awareness and adoption intent—an important behavioural signal in the Chinese context (Supplementary Note 4). Baidu is widely regarded as the Chinese analogue to Google and is a widely used search engine in China. Baidu's search query volumes are released to the public as a weighted indicator known as the Baidu Index (https://index.baidu.com). This index has been applied to forecasting transit ridership[42,43], modelling infectious-disease transmission[44] and predicting EV sales[45]. Together, these indicators capture demographic, economic, policy and behavioural dimensions that jointly shape EV uptake and battery retirements. We model passenger and commercial vehicles separately because these vehicle classes differ in usage scenarios, battery lifespan, retirement patterns and metal recovery potential. PEVs, primarily used for private short-distance commuting, have lower annual mileage and slower battery capacity degradation, with retirement cycles typically lasting 8–10 years. By contrast, CEVs (for example, logistics trucks and buses) operate under high-frequency, high-load conditions, accumulating annual mileages of 50,000–80,000 km, leading to faster capacity degradation and shorter retirement cycles (5–7 years). Additionally, battery installation ratios differ between the two vehicle types. By conducting independent modelling, this study can precisely capture the retirement dynamics of both vehicle categories and avoid prediction biases caused by mixed data. Data curation steps are detailed in Supplementary Note 6.

Second, given the systematic variations in characteristics across cities, we first embed and cluster cities using training-period statistics, obtaining a few internally homogeneous clusters. Models are then trained within each cluster, which improves data efficiency and reduces nationwide misspecification. Third, we compare four regressors within each cluster: support vector machines (Supplementary Note 7), random forests (Supplementary Note 8), extreme gradient boosting (Supplementary Note 9) and artificial neural networks (Supplementary Note 10). Two lightweight ensembles are added: (1) stacking uses time-ordered out-of-fold predictions from a single base learner as input to a linear meta-learner, improving stability while preventing leakage; and (2) BlendTop2 is a lightweight blending ensemble that combines the predictions of the two best-performing single models using fixed linear weights, thereby balancing bias and variance in small samples. The full workflow and parameter settings are provided in the Supplementary Information.

To evaluate the predictive performance of each machine learning model within clustered passenger and commercial vehicle groups, we adopted R^2 and NMSE as the primary evaluation metrics. R^2 provides an intuitive measure of explanatory power and goodness-of-fit, and enables a straightforward comparison across different model structures. By normalizing the mean square error, NMSE penalizes large deviations more heavily and, thus, captures occasional extreme errors, while also allowing error magnitudes to be compared across datasets of different scales.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

$$\mathrm{NMSE} = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

where n denotes the sample size, y_i represents the observed value of the i sample, $\hat{y}_i$ indicates the predicted value for the i sample from the model, $\bar{y}$ signifies the mean of all observed values, $\sum_{i=1}^{n}(y_i - \hat{y})^2$ calculates the residual sum of squares and $\sum_{i=1}^{n}(y_1 - \bar{y})^2$ computes the total sum of squares.

Furthermore, to assess robustness and generalizability, we complemented these metrics with out-of-sample and time-series extrapolation tests. Specifically, we performed rolling-origin cross-validation, training models on earlier years and testing them on later periods, thereby mimicking the temporal nature of forecasting. This procedure ensured that our reported model performance is not only reflective of in-sample fit but also indicative of predictive reliability under real-world forecasting conditions.

Based on the predicted registration volume of EVs, this study forecasts the city-level volumes of EOL power batteries by integrating battery-type proportions, battery characteristics and the Weibull survival distribution. The battery types considered include 24 categories derived from combinations of six battery chemistries (LFP, NCM111, NCM523, NCM622, NCM811 and nickel–cobalt–aluminium) and four vehicle categories (passenger plug-in hybrid EVs, passenger battery EVs, commercial plug-in hybrid EVs and commercial battery EVs). This results in six battery types and four vehicle categories, producing 24 combinations. The data on the installed capacity share of 24 types of batteries in China from 2016 to 2024 are shown in Supplementary Fig. 4. Owing to constraints in technological limitations, funding constraints and supply chain challenges, it remains challenging to achieve large-scale commercial adoption of new battery technologies such as solid-state and semi-solid-state batteries in the short term[46]. Therefore, given the timeframe of this study, the impact of these new battery installation volumes has not been considered.

The two-parameter Weibull distribution model, which best approximates the real-world operational conditions of power batteries, was employed for estimation. For battery chemistry type m, the Weibull distribution function can be expressed as $f_m(t)$, where t denotes time. The probability density function of the Weibull distribution is formulated as[47]:

$$f_m(t; k, \lambda) = \frac{k_m}{\lambda_m}\left(\frac{t}{\lambda_m}\right)^{k_m - 1} \mathrm{e}^{-\left(\frac{t}{\lambda_m}\right)^{k_m}} \tag{3}$$

where k_m is the shape parameter for battery chemistry type m, governing the distribution's curvature and retirement patterns. We adopt a shape factor k_m of 3.50 for all battery types, consistent with values reported in previous studies[25,48]. The corresponding scale parameter λ_m, which represents the characteristic lifetime of the battery type m, is shown in Supplementary Table 8 and Supplementary Fig. 6 (ref. 49).

In the BAU, dynamic lifetime trajectories were assumed for EVs. The parameter values for passenger and commercial vehicles during 2020–2030 are reported in Supplementary Table 24. Assumptions regarding battery replacement are adopted from the 2024 GREET model[50]. For battery-electric and hybrid-electric passenger vehicles, as well as CEVs, one replacement is assumed—the original pack is replaced once over the vehicle's lifetime, consistent with studies showing that vehicle lifetimes exceed battery lifetimes[8,27]. Accordingly, three retirement events were considered (only a single replacement event was permitted):

(i) $N_{\mathrm{orig_{EOL}}}(a, m)$ is the number of original batteries retiring with the vehicle at vehicle age a:

$$N_{\mathrm{orig_{EOL}}}(a, m) = N_{t_s,m} \times [F_v(a) - F_v(a-1)] \times [1 - F_b(a)] \tag{4}$$

(ii) $N_{\mathrm{repl}}(a, m)$ is the number of early battery failures and replacements at vehicle age a:

$$N_{\mathrm{repl}}(a, m) = N_{t_s,m} \times [F_b(a) - F_b(a-1)] \times [1 - F_v(a)] \tag{5}$$

(iii) $N_{\mathrm{repl}_{\mathrm{EOL}}}(a,m)$ is the number of replacement packs retired with the vehicle at vehicle age a. First, an original battery fails and is replaced at age r ($1 \le r < a$). Second, the vehicle, now equipped with the replacement battery, is retired at age a. The replacement battery's age at this point is $a - r$.

$N_{\mathrm{repl}_{\mathrm{EOL}}}(a,m)$ is determined by summing overall possible replacement ages r

$$N_{\mathrm{repl}_{\mathrm{EOL}}}(a,m) = \sum_{r=1}^{a-1} N_{\mathrm{repl}}(r,m) \times [1 - F_b(a-r)] \times \frac{F_v(a) - F_v(a-1)}{1 - F_v(r)} \quad (6)$$

$N_{\mathrm{total}}(a,m)$ denotes total retired batteries for the cohort at age:

$$N_{\mathrm{total}}(a,m) = N_{\mathrm{orig}_{\mathrm{EOL}}}(a,m) + N_{\mathrm{repl}}(a,m) + N_{\mathrm{repl}_{\mathrm{EOL}}}(a,m) \quad (7)$$

where t_s denotes the year of vehicle registration, t is the calculation year, N_{c,t_s} represents the number of EVs registered in city c during year t_s, $F_v(a)$ is the cumulative distribution function for vehicles after $a = t - t_s$ years, $F_b(a)$ is the cumulative distribution function for batteries after a years, w_m is the battery weight, C_m is the battery capacity for vehicle type m and $N_{t_s,m}$ represents vehicles of type m sold in year t_s, with the number of retired units at age a.

The retired battery weight $W_{c,t,m}$ for city c, year t and vehicle type m is calculated as:

$$W_{c,t,m} = \left(\sum_{t_s} N_{c,t_s,m} \times P_{\mathrm{total}}(t - t_s, m) \right) \times w_{m,t} \quad (8)$$

where $w_{m,t}$ uses the battery weight specifications of the retirement year, $P_{\mathrm{total}}(a,m) = N_{\mathrm{total}}(a,m)/N_{t_s,m}$ is the total retirement probability at age a and $N_{c,t_s,m}$ represents the initial number of type m vehicles sold in the city c during the year t_s.

$$\begin{aligned} E_{c,t,m} = {} & \textstyle\sum_{t_s} N_{c,t_s,m} \times \big(P_{\mathrm{orig}_{\mathrm{EOL}}}(a, m \times C_{m,t_s} \times d_m + P_{\mathrm{repl}}(a,m) \\ & \times C_{m,t} \times d_m + \textstyle\sum_{r=1}^{a-1} P_{\mathrm{repl}_{\mathrm{EOL}_r}}(a,m) \times C_{m,t_s+} \times d_m\big) \end{aligned} \quad (9)$$

where d_m denotes the attenuation coefficient of the battery, $P_{\mathrm{orig}_{\mathrm{EOL}}}(a,m)$, $P_{\mathrm{repl}}(a,m)$ and $P_{\mathrm{repl}_{\mathrm{EOL}_r}}(a,m)$ denote the respective probabilities of the three retirement scenarios, C_{m,t_s} is the capacity from the sales year t_s, $C_{m,t}$ is the capacity from the current year t and C_{m,t_s+r} is the capacity from the year of replacement $t_s + r$.

After forecasting the volumes of EOL power batteries across 364 cities from 2020 to 2030, we analysed their spatiotemporal distribution patterns. A gravity analysis method was applied to calculate the geographic centroid of battery retirement for each year during 2020–2030 using a weighted averaging approach. This method helps identify mobility trends and shifts in concentration areas of retired batteries. Collected data were input into an ArcGIS system and converted into formats suitable for spatial analysis, with each point representing the geographic location of retired batteries. For each time point, equations (10) and (11) were applied to quantify spatial dynamics[51]:

$$\bar{X} = \frac{\sum_{i=1}^{n} (X_i w_i)}{\sum_{i=1}^{n} w_i} \quad (10)$$

$$\bar{Y} = \frac{\sum_{i=1}^{n} (Y_i w_i)}{\sum_{i=1}^{n} w_i} \quad (11)$$

where X_i and Y_i denote the geospatial coordinates of geographic elements, $\bar{X}$ and $\bar{Y}$ are the coordinates of the weighted average centre of gravity and w_i represents the weighting factor for retired power batteries.

Cross-regional transportation simulation

We model battery flows among 364 Chinese cities for 2020–2030 by linking our city-level EV retirement framework and city-level recycling projects. City–city road distances are queried via the Gaode (Amap) API (https://lbs.amap.com) and adjusted by a detour factor (multiply by 1.30) to approximate actual haulage routes. City clusters follow national urban agglomerations and provincial adjacency is taken from administrative maps. For each origin city and year, the predicted EOL battery volume was first divided into formal and informal streams according to the calibrated formal collection share used in the BAU. Informal recycling was assumed to remain local, reflecting limited transport capacity and regulatory constraints, whereas formal recycling was allowed to access licensed facilities across administrative boundaries depending on the scenario design.

We simulated the following three cross-regional allocation scenarios for formal recyclers in addition to the baseline in-province case: (1) local radius recycling: batteries are transported within a 300 km radius to the nearest facility; (2) urban cluster collaboration: coordinated recycling across key city clusters (for example, Yangtze River Delta and Pearl River Delta); and (3) adjacent province allocation: batteries can be transferred to facilities in neighbouring provinces. Within each scenario, candidate destinations were screened according to the relevant spatial rule, and batteries were then assigned sequentially to the nearest eligible licensed city with available remaining capacity. This procedure generates city-to-city flow matrices and transport ton-kilometres, which were subsequently used to evaluate capacity matching and transport-related environmental burdens. Further implementation details are provided in Supplementary Notes 17 and 18.

Metal stock and environmental impact assessment

This LCA follows the principle of ISO 14040[52], including four steps: goal and scope definition, life-cycle inventory, life-cycle impact assessment and interpretation. The recycling processes were categorized based on actual treatment targets of lithium-ion battery chemistries—NCM and LFP batteries. Regional technology portfolio distributions were determined through analysis of environmental impact assessment reports from battery recycling projects. The recycling projects identified in our database exclusively treat retired EV batteries, and manufacturing offcuts or defective batteries from the production stage were excluded. Recyclers were classified into three emission tiers (low, medium and high) using publicly available specifications for equipment and process characteristics, together with national regulatory compliance thresholds. Recovery technologies were categorized into the following eight representative categories according to process route, feedstock chemistry and emission magnitude (Supplementary Note 20): (1) low-emission pyro-hydrometallurgy for NCM[53]; (2) low-emission hydrometallurgy for NCM[54]; (3) low-emission hydrometallurgy for LFP[53]; (4) medium-emission hydrometallurgy for NCM[55]; (5) medium-emission pyrometallurgy for LFP[56]; (6) high-emission hydrometallurgy for NCM[57]; (7) high-emission hydrometallurgy for LFP[58]; and (8) high-emission pyrometallurgy for NCM[59].

LCA is a method used to evaluate the environmental impacts of products, processes or services throughout their life cycles[60]. This study conducts a life-cycle analysis of power battery recycling stages based on the ISO 14044 standard[61]. The system boundary primarily encompasses battery transport, pre-processing and disassembly during the treatment stage, energy and material inputs, metal recovery and EOL waste management. The system-boundary diagram is provided in Supplementary Fig. 5.

This study integrates geospatial data, installed recycling capacities and enterprise-type counts to quantify temporal changes in city-level recycling-process shares, simulate metal recovery efficiency and estimate environmental impacts. The frequent neglect of regional heterogeneity in prior LCA studies is addressed. Background data are sourced from the ecoinvent 3.9.1 database, which provides life-cycle inventory data for chemicals, electricity generation and auxiliary inputs. In addition, provincial emission factors for electricity generation are derived from a literature-based, province-specific electricity-mix configuration[62]. Process-level life-cycle inventories are provided in Supplementary Tables 12–22.

This study employs the CML-IA methodology implemented through openLCA software[63] to evaluate eight recycling processes, selecting the following ten environmental impact indicators for assessment (Supplementary Table 25): abiotic resource depletion—elements, abiotic resource depletion—fossil fuels, GWP over a 100-year timeframe, AP, EP, HTP, photochemical oxidation potential, ozone layer depletion potential, terrestrial ecotoxicity potential and marine aquatic ecotoxicity potential. GWP, AP, EP and HTP are used as the primary indicators, and the remaining indicator datasets are archived in the Supplementary Information. In addition, to assess the consistency between the IPCC AR6 characterization of GWP (100a) and the CML method, results from both methods are compared, and only minor differences are observed (Supplementary Table 27).

Spatially integrated scenario modelling

This study formulates scenarios encompassing supply-side battery technology evolution pathways and demand-side market dynamics. The supply-side framework incorporates four nationally implemented battery technology transformation scenarios: (1) BAU: maintaining current technological trajectories; (2) TP: prioritizing NCM battery dominance; (3) ED: improving battery energy capacity; and (4) LE: prolonging battery service cycles.

The demand-side framework comprises five regionally differentiated core scenarios: (1) BAU: continuing existing market patterns; (2) ES: energy structure adjustment aligned with national decarbonization targets[62]; (3) AR: channelling batteries to certified recyclers[18]; (4) TO: consideration of thermodynamic limits[64] (Supplementary Note 19), optimization of energy use across processes and increases in metal recovery rates (Supplementary Table 29); and (5) SU: implementing cascaded battery applications[65]. For the fourth scenario, TO, three intensities are considered—100%, 60% and 30%—for the thermodynamic-limit adjustment. At 100%, all foreground life-cycle inventory entries are replaced by their thermodynamic minima, and at both 60% and 30%, each entry is reduced by 60% or 30% of the difference between the baseline value and its thermodynamic minimum. The AR and SU scenarios implement three intensity levels (20%, 40% and 60%), while the ES scenario stratifies into the following scenarios: high-carbon scenario (traditional fossil fuel reliance without climate targets), medium-carbon scenario (2 °C-aligned transitional pathway) and low-carbon scenario (1.5 °C-compliant sustainable development pathway). This generates 52 combinatorial scenarios (detailed in Extended Data Table 1). The BAU extrapolates 2024 battery market conditions, while TP emphasizes NCM battery proliferation. AR incentivizes formal recycling networks, TO incorporates advanced metallurgical processes and SU promotes extended battery value chains through repurposing applications.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The dataset necessary to interpret, verify and reproduce the main findings of this study is available in the Supplementary Information and the public sources listed below. Publicly accessible input data were obtained from the Baidu Index platform, the Ministry of Industry and Information Technology of China and city-level statistical bulletins on national economic and social development. Information on municipal recycling technologies and city-level treatment capacities was compiled from the China Project Development Network (accessed in December 2024), and enterprise classification data were obtained from the TianYanCha business registry. Background life-cycle inventory data were obtained from ecoinvent v.3.9.1 and TianGong LCA, subject to the access conditions of the respective databases. Data originating from third-party platforms that cannot be redistributed directly should be obtained from the original providers. Source data are provided with this paper.

Code availability

The Python code used for machine learning prediction, cross-regional flow simulation, scenario analysis and figure generation in this study is publicly available via GitHub at https://github.com/Miffyfei/EOL-Power-Battery-Recycling-Industry.git.

References

1. Harper, G. et al. Recycling lithium-ion batteries from electric vehicles. *Nature* **575**, 75–86 (2019).
2. Cheng, A. L., Fuchs, E. R. H. & Michalek, J. J. US industrial policy may reduce electric vehicle battery supply chain vulnerabilities and influence technology choice. *Nat. Energy* **9**, 1561–1570 (2024).
3. IEA. *Global EV Outlook 2024 – Analysis* https://www.iea.org/reports/global-ev-outlook-2024 (2024).
4. China's new energy vehicle production and sales both exceed 12 million units in 2024. *Xinhua News Agency* https://www.gov.cn/yaowen/liebiao/202501/content_6998270.htm (31 January 2025).
5. Zahoor, A. et al. Can the new energy vehicles (NEVs) and power battery industry help China to meet the carbon neutrality goal before 2060?. *J. Environ. Manage.* **336**, 117663 (2023).
6. Department of Electronic Information. *Operation Status of China's Lithium-Ion Battery Industry in 2023;* https://wap.miit.gov.cn/gxsj/tjfx/dzxx/art/2024/art_7de3ac5f07514eec80039a81aa2e22d8.html (2024).
7. Yu, W., Guo, Y., Shang, Z., Zhang, Y. & Xu, S. A review on comprehensive recycling of spent power lithium-ion battery in China. *eTransportation* **11**, 100155 (2022).
8. Zhang, B. et al. Lithium-ion battery recycling relieves the threat to material scarcity amid China's electric vehicle ambitions. *Nat. Commun.* **16**, 6661 (2025).
9. Nan, S. The construction of a key mineral recovery system is urgently needed. *China Energy News* https://doi.org/10.28693/n.cnki.nshca.2024.000821 (2024).
10. Ma, R. et al. Pathway decisions for reuse and recycling of retired lithium-ion batteries considering economic and environmental functions. *Nat. Commun.* **15**, 7641 (2024).
11. Tian, X. et al. Management of spent power batteries in China: progress, policies, and challenges. *Renew. Sustain. Energy Rev.* **219**, 115797 (2025).
12. Kite, A. Fire erupts in southeast Missouri at one of world's largest lithium-ion battery facilities. *Missouri Independent* https://missouriindependent.com/briefs/fire-erupts-in-southeast-missouri-at-one-of-worlds-largest-lithium-ion-battery-facilities (30 October 2024).
13. EVTank, China YiWei Institute of Economics, & China Battery Industry Association. *China Lithium-Ion Battery Recycling, Dismantling, and Cascade Utilization Industry Development*; White Paper http://www.evtank.cn/DownloadDetail.aspx?ID=556 (27 March 2024).
14. Chen, L. & Gao, M. Formal or informal recycling sectors? Household solid waste recycling behavior based on multi-agent simulation. *J. Environ. Manage.* **294**, 113006 (2021).
15. Huang, X. et al. Consumer preference and willingness-to-pay for formal recycling of electric vehicle batteries: a discrete choice experiment in China. *J. Environ. Manage.* **370**, 122180 (2024).
16. Song, L. et al. China's bulk material loops can be closed but deep decarbonization requires demand reduction. *Nat. Clim. Change* **13**, 1136–1143 (2023).

17. Engels, P. et al. Life cycle assessment of natural graphite production for lithium-ion battery anodes based on industrial primary data. *J. Clean. Prod.* **336**, 130474 (2022).
18. Tian, X., Peng, F., Xie, J. & Liu, Y. Agent-based modeling for an end-of-life power battery cross-regional recycling system and subregional policy analysis: a case study in China. *J. Clean. Prod.* **441**, 141054 (2024).
19. Greenhouse Gas Protocol. Standards and guidance; https://ghgprotocol.org/standards-guidance (2022).
20. International Organization for Standardization. *ISO 14064-1:2018 Greenhouse Gases – Part 1: Specification with Guidance at the Organization Level for Quantification and Reporting of Greenhouse Gas Emissions and Removals* https://www.iso.org/standard/66453.html (2018).
21. Tian, X., Ma, Q., Xie, J., Xia, Z. & Liu, Y. Environmental impact and economic assessment of recycling lithium iron phosphate battery cathodes: comparison of major processes in China. *Resour. Conserv. Recycl.* **203**, 107449 (2024).
22. Liu, Z. et al. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* **524**, 335–338 (2015).
23. Ministry of Ecology and Environment. *Database of National Greenhouse Gas Emission Factor* https://data.ncsc.org.cn/factoryes/index (2025).
24. Ministry of Industry and Information Technology of the People's Republic of China. Interpretation of the 'Industry normative conditions for comprehensive utilization of waste power batteries from new energy vehicles (2024 edition)'; https://www.gov.cn/zhengce/202412/content_6994289.htm (2024).
25. Yang, D. et al. Evaluating the recycling potential and economic benefits of end-of-life power batteries in China based on different scenarios. *Sustain. Prod. Consum.* **47**, 145–155 (2024).
26. Zeng, X., Ali, S. H. & Li, J. Estimation of waste outflows for multiple product types in China from 2010–2050. *Sci. Data* **8**, 15 (2021).
27. Wang, C. et al. Urban stock-demography approach to uncover electric vehicle battery and embedded lithium stock across 366 cities in China. *Ecosyst. Health Sustain.* **11**, 0297 (2025).
28. Wu, Y. et al. Impact of circular economy on the long-term allocation structure of primary and secondary lithium. *Commun. Earth Environ.* **5**, 503 (2024).
29. Gong, W. T., Daigo, I., Dunuwila, P. & Sun, X. The change of material flows and environmental impacts along with future upgrading scenarios of NCM battery in China. *J. Clean. Prod.* **463**, 142758 (2024).
30. Zhang, C., Zhao, X., Sacchi, R. & You, F. Trade-off between critical metal requirement and transportation decarbonization in automotive electrification. *Nat. Commun.* **14**, 1616 (2023).
31. Deng, F. et al. A big data approach to improving the vehicle emission inventory in China. *Nat. Commun.* **11**, 2801 (2020).
32. Yin, R., Hu, S. & Yang, Y. Life cycle inventories of the commonly used materials for lithium-ion batteries in China. *J. Clean. Prod.* **227**, 960–971 (2019).
33. Zhang, W. et al. Analyzing the environmental impact of copper-based mixed waste recycling-a LCA case study in China. *J. Clean. Prod.* **284**, 125256 (2021).
34. The Central People's Government of the People's Republic of China. *Notice on Carrying Out Pilot Eork for Demonstration and Promotion of Energy-Saving and Electric Vehicles*; https://www.mof.gov.cn/gp/xxgkml/jjjss/200902/t20090210_2499581.html (2009).
35. Tan, Q., Li, J., Yang, L. & Xu, G. Cascade use potential of retired traction batteries for renewable energy storage in China under carbon peak vision. *J. Clean. Prod.* **412**, 137379 (2023).
36. Wang, S. & Yu, J. Evaluating the electric vehicle popularization trend in China after 2020 and its challenges in the recycling industry. *Waste Manag. Res.* **39**, 818–827 (2021).
37. Star Island News Group. Key contributor behind CATL overcomes the challenge of 'waste recycling and recovery', helping build a battery circular ecosystem. *Sing Tao Daily Global Network* https://www.stnn.cc/c/2025-05-16/3981048.shtml (2025).
38. Ciez, R. E. & Whitacre, J. F. Examining different recycling processes for lithium-ion batteries. *Nat. Sustain.* **2**, 148–156 (2019).
39. Chen, Q. et al. Investigating the environmental impacts of different direct material recycling and battery remanufacturing technologies on two types of retired lithium-ion batteries from electric vehicles in China. *Sep. Purif. Technol.* **308**, 122966 (2023).
40. Peiseler, L. et al. Carbon footprint distributions of lithium-ion batteries and their materials. *Nat. Commun.* **15**, 10301 (2024).
41. Tian, X. et al. China-specific unit process dataset for lithium-ion batteries. *Resour. Conserv. Recycl.* **211**, 107886 (2024).
42. Jin, K., Sun, S., Li, H. & Zhang, F. A novel multi-modal analysis model with Baidu Search Index for subway passenger flow forecasting. *Eng. Appl. Artif. Intell.* **107**, 104518 (2022).
43. Li, H., Li, X., Sun, S., Huang, Z. & Jia, X. Multivariable forecasting approach of high-speed railway passenger demand based on residual term of Baidu Search Index and error correction. *J. Forecast.* **43**, 2401–2433 (2024).
44. Liu, K. et al. Using Baidu Search Index to predict dengue outbreak in China. *Sci. Rep.* **6**, 38040 (2016).
45. Tan, T., Huang, Z. T., Lin, Y. L. & Bi, G. C. Big data driven demand analysis of new energy vehicles. *Renew. Energy Resour.* **38**, 967–971 (2020).
46. Frith, J. T., Lacey, M. J. & Ulissi, U. A non-academic perspective on the future of lithium-based batteries. *Nat. Commun.* **14**, 420 (2023).
47. Ai, N., Zheng, J. & Chen, W. Q. U.S. end-of-life electric vehicle batteries: dynamic inventory modeling and spatial analysis for regional solutions. *Resour. Conserv. Recycl.* **145**, 208–219 (2019).
48. Jiang, R. et al. Impact of electric vehicle battery recycling on reducing raw material demand and battery life-cycle carbon emissions in China. *Sci. Rep.* **15**, 2267 (2025).
49. Wu, Y., Yang, L., Tian, X., Li, Y. & Zuo, T. Temporal and spatial analysis for end-of-life power batteries from electric vehicles in China. *Resour. Conserv. Recycl.* **155**, 104651 (2020).
50. R&D GREET Model. *Argonne National Laboratory* https://greet.anl.gov (2024).
51. Duman, Z. et al. Exploring the spatiotemporal pattern evolution of carbon emissions and air pollution in Chinese cities. *J. Environ. Manage.* **345**, 118870 (2023).
52. International Organization for Standardization. *ISO 14040: Environmental Management – Life Cycle Assessment – Principles and Framework* (2006).
53. Tao, Y., Wang, Z., Wu, B., Tang, Y. & Evans, S. Environmental life cycle assessment of recycling technologies for ternary lithium-ion batteries. *J. Clean. Prod.* **389**, 136008 (2023).
54. Jiang, S. et al. Environmental impacts of hydrometallurgical recycling and reusing for manufacturing of lithium-ion traction batteries in China. *Sci. Total Environ.* **811**, 152224 (2022).
55. Quan, J. et al. Comparative life cycle assessment of LFP and NCM batteries including the secondary use and different recycling technologies. *Sci. Total Environ.* **819**, 153105 (2022).
56. Yu, A., Wei, Y., Chen, W., Peng, N. & Peng, L. Life cycle environmental impacts and carbon emissions: a case study of electric and gasoline vehicles in China. *Transp. Res. Part Transp. Environ.* **65**, 409–420 (2018).
57. Feng, T., Guo, W., Li, Q., Meng, Z. & Liang, W. Life cycle assessment of lithium nickel cobalt manganese oxide batteries and lithium iron phosphate batteries for electric vehicles in China. *J. Energy Storage* **52**, 104767 (2022).
58. Wang, Y. et al. Environmental impact assessment of second life and recycling for LiFePO4 power batteries in China. *J. Environ. Manage.* **314**, 115083 (2022).

59. Liu, M., Liu, W., Liu, W., Chen, Z. & Cui, Z. To what extent can recycling batteries help alleviate metal supply shortages and environmental pressures in China?. *Sustain. Prod. Consum.* **36**, 139–147 (2023).
60. Zhong, Y. et al. Carbon emissions from urban takeaway delivery in China. *Npj Urban Sustain.* **4**, 39 (2024).
61. International Organization for Standardization. *ISO 14044: Environmental Management – Life Cycle Assessment – Requirements and Guidelines* (2006).
62. Tang, J. et al. Deciphering decarbonization trajectories in China by spatiotemporal-accumulation modeling of electricity carbon footprint. *iScience* **28**, 111963 (2025).
63. Sabet, H., Moghaddam, S. S. & Ehteshami, M. A comparative life cycle assessment (LCA) analysis of innovative methods employing cutting-edge technology to improve sludge reduction directly in wastewater handling units. *J. Water Process Eng.* **51**, 103354 (2023).
64. Bolson, N., Cullen, L. & Cullen, J. A robust framework for estimating theoretical minimum energy requirements for industrial processes. *Energy* **322**, 135411 (2025).
65. Aguilar Lopez, F., Lauinger, D., Vuille, F. & Müller, D. B. On the potential of vehicle-to-grid and second-life batteries to provide energy and material security. *Nat. Commun.* **15**, 4179 (2024).
66. National Administration of Surveying, Mapping and Geoinformation. *Standard Map Service* http://bzdt.ch.mnr.gov.cn/browse.html?picId=%224o28b0625501ad13015501ad2bfc2187%22 (Ministry of Natural Resources Map Technology Review Center & China Map Publishing House, 2023).
67. Zeng, A. et al. Battery technology and recycling alone will not save the electric mobility transition from future cobalt shortages. *Nat. Commun.* **13**, 1341 (2022).
68. Jiang, S. et al. Assessment of end-of-life electric vehicle batteries in China: future scenarios and economic benefits. *Waste Manag.* **135**, 70–78 (2021).
69. Dou, Y., Song, X., Zhuang, X., Wu & Fan, S. Life cycle assessment and carbon reduction scenario analysis of retired lithium iron phosphate batteries for cascade utilization. *China Environ. Sci.* **44**, 4091–4100 (2024).
70. Ministry of Industry and Information Technology. *Announcement No. 42 of 2024 issued by the Ministry of Industry and Information Technology of the People's Republic of China*; https://www.miit.gov.cn/zwgk/zcwj/wjfb/gg/art/2024/art_2ca9a4ed31de469d9da26ca70c83a868.html (2024).

Acknowledgements

The authors gratefully acknowledge the financial support of the Royal Society ISPF International Collaboration Awards (ICA\R1\231046), Saudi Aramco Technologies Company, National Natural Science Foundation of China (grant 52270181), Jiangxi Province Key R&D Plan Projects (grant 20232BBG70005) and Jiangxi Provincial Natural Science Foundation for Distinguished Young Scholars (grant 20242BAB23050). For the purpose of open access, the author has applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission.

Author contributions

X.T. contributed to conceptualization, data curation, investigation, methodology, supervision and writing and reviewing. F.P. contributed to conceptualization, visualization, data curation, investigation, methodology and writing and reviewing. J.M. contributed to visualization and writing and reviewing. A.F.N.A.-M. contributed to visualization and writing and reviewing. Y.L. contributed to data curation, visualization and writing and reviewing. F.M. contributed to data curation, investigation, methodology, supervision and writing and reviewing.

Competing interests

A.F.N.A.-M. is employed by Saudi Aramco. The other authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41893-026-01851-6.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-026-01851-6.

Correspondence and requests for materials should be addressed to Fanran Meng.

Peer review information *Nature Sustainability* thanks Xi Chen, Alissa Kendall, Shen Qu, Yuan Yao and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Extended Data Table 1 | Battery supply-side and corporate demand-side scenario settings

Category	Scenario Name	Abb.	Scenario Description and Key Parameters
Supply-Side	Base Scenario	BAU	Maintains 2024 battery characteristics (battery types, capacity, weight, metal content, etc.)
	Battery Type Proportion Adjustment[67]	TP	Starting in 2024, gradually increase the annual installed capacity share of NCM batteries until 2030, when the battery installation will be entirely NCM.
	Energy Density Improvement	ED	Starting in 2024, it enhances energy density across 24 battery types, increasing it by 3.6% each year[28].
	Lifespan Extension	LE	This extends the lifespan of 24 battery types. Starting in 2024, the battery life will increase by 10% each year. The maximum limit is set at 15 years by 2030[68].
Demand-Side	Base Scenario	BAU	Preserves 2023 market conditions (energy mix ratios, implemented technologies, recycling methods, enterprise quantities, recovery rates)
	Electricity Structure Evolution[62]	ES	ES3: Low-Carbon Scenario (1.5 °C-compliant sustainable development pathway)
			ES2: Medium-Carbon Scenario (2 °C-aligned transitional pathway)
			ES1: High-Carbon Scenario (Traditional fossil fuel reliance without climate targets)
	Authorized recycling[18]	AR	AR3: Annual 60% reduction in informal workshop recycling
			AR2: Annual 40% reduction in informal workshop recycling
			AR1: Annual 20% reduction in informal workshop recycling
	Technological Optimization[28]	TO	TO3: 100% thermodynamic-limit scenario: All foreground life-cycle inventory entries are directly replaced by their thermodynamic minimum values.
			TO2: 60% thermodynamic-limit scenario: Each life-cycle inventory entry is adjusted by moving 60% of the gap between the baseline value and the thermodynamic minimum value.
			TO1: 30% thermodynamic-limit scenario: Each life-cycle inventory entry is adjusted by moving 30% of the gap between the baseline value and the thermodynamic minimum value.
	Secondary Utilization for LFP[25,69]	SU	SU3: 60% annual cascade utilization rate
			SU2: 40% annual cascade utilization rate
			SU1: 20% annual cascade utilization rate

The numerals 1, 2, and 3 are used to denote the Conservative, Moderate, and Aggressive scenarios, respectively. The scenario analysis excluded commercial-scale production of emerging battery technologies as the research timeframe (2016-2030) predates the projected 2025 commencement of next-generation battery commercialization[11,46], while solid-state batteries' operational lifespans (substantially exceeding five years) would extend beyond the study's temporal scope. *The Technical Specifications for Comprehensive Utilization of Retired Power Batteries from New Energy Vehicles (2024 Revision)* mandates that annual cascade utilization volumes must account for ≥60% of total retired battery collections[70].

nature portfolio

Corresponding author(s): Fanran Meng

Last updated by author(s): Apr 22, 2026

Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☒	☐	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☒	☐	A description of all covariates tested
☒	☐	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☒	☐	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☒	☐	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Baidu Index data were collected via Python web crawling from: https://index.baidu.com/v2/index.html#/. The geographical coordinates (latitude and longitude) of the enterprise are obtained through the Amap API. The other data collection was all obtained manually. Specific codes and data are available in our GitHub repository: https://github.com/Miffyfei/EOL-Power-Battery-Recycling-Industry.git
Data analysis	Data analysis was conducted using openLCA 2.2.0, ArcGIS (version 10.5), Python (3.11), and Origin (version 2025).

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

The dataset necessary to interpret, verify and reproduce the main findings of this study is available through the Source Data files provided with this paper, the Supplementary Information, and the public sources listed below. Source Data are provided for the main figures containing plotted data. Publicly accessible input data were obtained from the Baidu Index platform, the Ministry of Industry and Information Technology of China, and city-level Statistical Bulletins on National Economic and Social Development. Information on municipal recycling technologies and city-level treatment capacities was compiled from the China Project Development Network (accessed in December 2024), and enterprise classification data were obtained from the TianYanCha business registry. Background life cycle inventory data were obtained from ecoinvent v3.9.1 and TianGong LCA, subject to the access conditions of the respective databases. Data originating from third-party platforms that cannot be redistributed directly should be obtained from the original providers. The Supplementary Information contains Supplementary Notes 1-20, Supplementary Tables 1-32, Supplementary Figures 1-9, and additional references.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	This job does not include this aspect.
Reporting on race, ethnicity, or other socially relevant groupings	This job does not include this aspect.
Population characteristics	This job does not include this aspect.
Recruitment	This job does not include this aspect.
Ethics oversight	This job does not include this aspect.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We use machine learning to project the spatiotemporal distribution patterns of rising EOL battery across 364 cities in China and match them with a provincial-level life cycle assessment to characterise the environmental impacts of over 300 heterogeneous battery recycling projects covering 24 battery types.
Research sample	This study covers 364 mainland Chinese cities, including (full list in Table S1): Provincial-level municipalities (4), Prefecture-level cities (293), Administrative regions (7), Autonomous prefectures (30), Leagues (3), County-level cities directly governed by provinces (27). Data from Taiwan (China), Hong Kong (China), Macau (China), and the cities of Kekdala, Kunyu, Huyanghe, Xinxing, and Baiyang in the Xinjiang Uygur Autonomous Region were excluded due to data availability limitations.
Sampling strategy	We have developed 52 simulated scenarios across three levels, aggressive, moderate, and conservative, by integrating battery technology development on the supply side with recycling market demand scenarios.
Data collection	The detailed information were included in the Manuscript and Supplementary information.
Timing and spatial scale	The time span is from 2016 to 2030, and the spatial scale is 364 cities in Chinese mainland. Due to the difficulty in obtaining data from Hong Kong, Macao and Taiwan of China, they were not taken into consideration.
Data exclusions	No data were excluded from the analyses.
Reproducibility	All attempts to repeat the experiment were successful. The Python code implementing machine learning prediction algorithms alongside scenario-based uncertainty simulations for the 2020-2030 period has been made available via https://github.com/Miffyfei/EOL-Power-Battery-Recycling-Industry.git
Randomization	This study does not involve random selection. To ensure transparency and reproducibility of results, all methods and calculation processes are fixed.
Blinding	Blinding was not relevant to our study, and all the detests analyzed in this study are publicly available as referenced within the article.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern
☒	☐ Plants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks	This job does not include this aspect.
Novel plant genotypes	This job does not include this aspect.
Authentication	This job does not include this aspect.