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Environmental, social and economic justice of data centers on urban sustainability

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Abstract. The rapid expansion of data centers in Los Angeles metropolitan, raises critical questions about urban sustainability. This study provides a comprehensive multi-dimensional data center sustainability index (**DCSI**): social, economic, and environmental of data center which is the network centre and strategic highland. We classify data centers to residential mid-sized, industrial hyper-scale and vertical colocation hubs. Take Los Angeles metropolitan as case study, in long beach community, the partial coefficient of distance to data center and housing prices per area is positive ($\beta=0.3881$, $t=1.12$). The noise created by data centers in El Segundo community can make citizens unbearable in radius of approximately 162m, 248m and 565m during daytime, night and summer night respectively. In downtown, vertical colocation hubs can aggravate urban heat island. For example, the One Wilshire which is the core landing station of the global submarine optical cable on the west coast of the United States, heat the area with the radius of 0.46km, 1.38km, 2.31km by 2°C, 1°C and 0.5°C respectively, the actual situation is determined by the height of the building and the direction of the street. However, this commercial use can also promote the value-added of real estate. All of them in case study consume 3,364GWh electricity each year, equal to more than 5.54% electricity generated by the whole metropolitan challenging the power system and clean energy. This study also explores that data centers cause approximately 1,549,824 tons CO₂ at the current scale each year, equal to 0.88% of the carbonisation of vegetation in Los Angeles metropolitan and it keeps growing. We conclude that unchecked data center growth risks undermining urban livability in Los Angeles. Policy recommendations include stricter siting regulations, mandatory noise and heat mitigation standards, and integration of green infrastructure to offset carbon impacts. This research offers timely insights for cities navigating the tension between digital transformation and sustainable urban futures.

The rapid advancement of artificial intelligence (AI) is profoundly reshaping urban landscapes and city systems worldwide⁵². At the core of this transformation are data centers, the critical physical infrastructure that underpins the explosive growth in computational power required for modern AI applications⁶⁸. Global data center electricity consumption reached approximately 415 TWh in 2024, accounting for roughly 1.5% of worldwide electricity use, with projections indicating it could more than double to around 945 TWh by 2030 as AI workloads intensify⁹. Hyperscale facilities are increasingly concentrating in and around major cities, driving significant urban implications across society (e.g., public perceptions and community dynamics), the environment (e.g., energy demand, water use, waste heat, and emissions), and local economies (e.g., effects on housing markets, commercial land values, and infrastructure costs). As cities navigate the opportunities and challenges of the AI era, understanding the urban footprint of data centers is essential for fostering sustainable and resilient urban development^{52,68}.

The distribution of data centers is shaped by energy supply, infrastructure, land cover and so on^{3,57,66}. It can also determines where the relative industries and enterprises go¹⁴. Data centers in urban environments can be classified into three primary morphological and locational models¹⁵. Residential mid-sized facilities are typically embedded in or adjacent to residential neighborhoods, often adapted from existing commercial buildings with limited footprints. Industrial hyperscale campuses consist of large-scale, single-story developments in suburban industrial zones, characterized by extensive land consumption and high-voltage power access. In contrast, vertical colocation hubs occupy multi-story structures in dense downtown areas, capitalizing on proximity to fiber networks and subsea cable landings for low-latency interconnection rather than sheer scale. These distinct models generate varied urban impacts: residential mid-sized projects frequently encounter NIMBY resistance due to noise and visual concerns, while industrial

hyperscale facilities reshape suburban land markets and infrastructure demands, and vertical hubs intensify pressure on central business districts^{1,10}.

Residential mid-sized data centers, often situated within or adjacent to neighborhoods, tend to generate localized socio-environmental pressures. These facilities often lead to mixed or negative impacts on nearby residential property values and land appreciation, as communities weigh the trade-offs between potential tax revenues and disruptions to living environments^{1,4,10,15,45}. Such developments also intensify local resource pressures, particularly through elevated water consumption for cooling in densely populated areas^{12,26}. Air quality and health concerns further arise from emissions and operational byproducts, compounding perceived risks for residents^{18,22,41,51}. They also significantly increase wholesale electricity prices²⁷. Consequently, these projects frequently trigger strong public opposition and environmental justice debates, as social media discourse and community sentiment highlight tensions between technological progress and quality of life in urban neighborhoods^{17,40,56}.

Industrial hyperscale campuses in suburban zones are major drivers of regional energy consumption and exert substantial pressure on local electricity markets and carbon emissions. These large-scale facilities significantly contribute to elevated greenhouse gas emissions through their massive and continuous power demand^{41,55,60,65}. It puts forward higher requirements for traditional energy systems^{8,23,35}. Its distribution is also shaped by many parameters like energy infrastructure^{24,29,61}. Urban and energy planners have measured the energy consumption by public sentiment⁵⁶, and explored new storage methods to increase efficiency and decrease the cost⁵⁸. At the same time, they present both challenges and opportunities for urban sustainability¹¹, economic resilience^{6,31} and decarbonization efforts³³, as cities and regions experiment with green data center pilots and renewable integration strategies to mitigate long-term environmental burdens^{34,42,63}. To address these issues, operators are increasingly adopting advanced infrastructure, cooling technologies^{13,19}, and operational optimization approaches, such as geo-distributed load balancing^{28,55} and multi-energy system integration^{49,67}, although full-scale implementation in industrial settings remains uneven.

Vertical colocation hubs housed within office buildings emit continuous concentrated waste heat, exacerbating localized urban heat island effects with prominent nighttime temperature rises driven by uninterrupted server and cooling loads^{38,40,46}. Confined hot exhaust brings multiple thermal hazards: accelerated degradation of building exteriors, electrical infrastructure and fire protection systems, deteriorated thermal comfort for office staff and nearby residents, and stagnant hot-humid microenvironments that degrade local air quality. Meanwhile, these hubs deliver substantial regional economic gains: they draw digital economy firms, generate consistent long-term municipal tax income^{1,15,62}, and create a full spectrum of high-skill IT, network and facility management jobs plus supporting operational roles, establishing a reliable engine for local employment and fiscal growth in central urban districts.

Urban infrastructure can shape how we experience life in cities⁴⁷. The development of data centers also raises critical questions of environmental, social, and economic justice, shaped by policy, regulatory, and geopolitical dynamics^{32,53,64}. Los Angeles is no exception. GIS is used in urban infrastructure site selection with multi-criteria decision algorithm^{36,54}, including data centers²⁵. Governance frameworks in the United States, while aiming to balance innovation with sustainability, often struggle with unprecedented demand growth, leading to uneven distribution of benefits and burdens across communities^{5,16,30,59,69}. In the Chinese context, national policies such as computing power infrastructure deployment and the East-West Computing Resources Transmission Project illustrate alternative approaches to spatial optimization and talent migration, offering comparative lessons for managing justice concerns in rapidly urbanizing digital economies^{14,21,48,70}. Meanwhile, supply chain barriers in AI adoption further complicate equitable outcomes, particularly regarding access to critical resources and technology³⁷. Overall, these governance and policy dimensions highlight the need for more inclusive frameworks that address environmental justice in residential areas, economic disparities in industrial zones, and social equity in vertical urban hubs, ensuring that the benefits of data center growth in cities like Los Angeles are more equitably shared.

While existing research has examined the broad energy, economic, policy and environmental impacts of data centers, significant gaps remain in understanding their differentiated effects across residential, industrial, and vertical urban typologies and their implications for environmental, social, and economic justice in specific metropolitan contexts. Few studies provide fine-grained,

multi-dimensional analyses that integrate spatial distribution with community socioeconomic indicators in major hubs like Los Angeles. This study addresses these gaps by offering a place-based examination of data center justice in the Los Angeles metropolitan area. This study focuses on different type data centers in Los Angeles metropolitan (case study). The residential mid-size data centers are researched about the community tolerance, noise and influence on Housing prices by empirical analysis. The colocation hubs in CBD are researched about the urban heat island effect and commercial profit from the land transfer. And finally, the energy consumption and carbon emissions are for all data centers in Los Angeles. This study divides data centers to three types and analysis these environmental, social and economical justice by constructing the data center sustainability index (*DCSI*), to balance the development of AI infrastructure and the habitat where we live.

Case Study

Los Angeles, California, offers a compelling case study of hyperscale data center clustering in a major coastal metropolis. As illustrated in Fig. 1, the Los Angeles metropolitan area hosts 71 data centers with a combined power capacity of approximately 358 MW. These facilities exhibit pronounced spatial concentration, particularly in Downtown LA (highlighted in the red frame), where legacy telecommunications infrastructure has evolved into a critical network hub⁷.

The iconic One Wilshire Building stands out as one of the most significant interconnection points on the West Coast and in the United States. This 30-story structure serves as a landing point for over 300 fiber optic lines and multiple Pacific submarine cables, facilitating high-volume internet traffic for global platforms such as Netflix and Amazon. This central agglomeration reflects path-dependent development driven by fiber optic connectivity and proximity to existing telecommunications infrastructure. In recent years, new data center clusters have emerged in peripheral locations, notably El Segundo to the west (adjacent to Los Angeles International Airport) and Monterey Park to the east. These expansions are likely influenced by available land, power access, and lower density compared to the urban core, while still benefiting from the region's robust digital infrastructure backbone.

This spatial pattern in Los Angeles exemplifies broader trends in data center geography: initial clustering around legacy network nodes followed by peripheral dispersal driven by land availability and power constraints. However, such concentration raises important local challenges, including increased electricity demand, potential urban heat island effects from waste heat, and competition for commercial land use, issues that resonate with national debates on data center siting, energy sustainability, and urban resilience. For instance, the two hollow pentagons in Monterey Park are DigiCo LAX1, 2 that have been rejected by citizens because of the noise, energy prices and potential pollution.

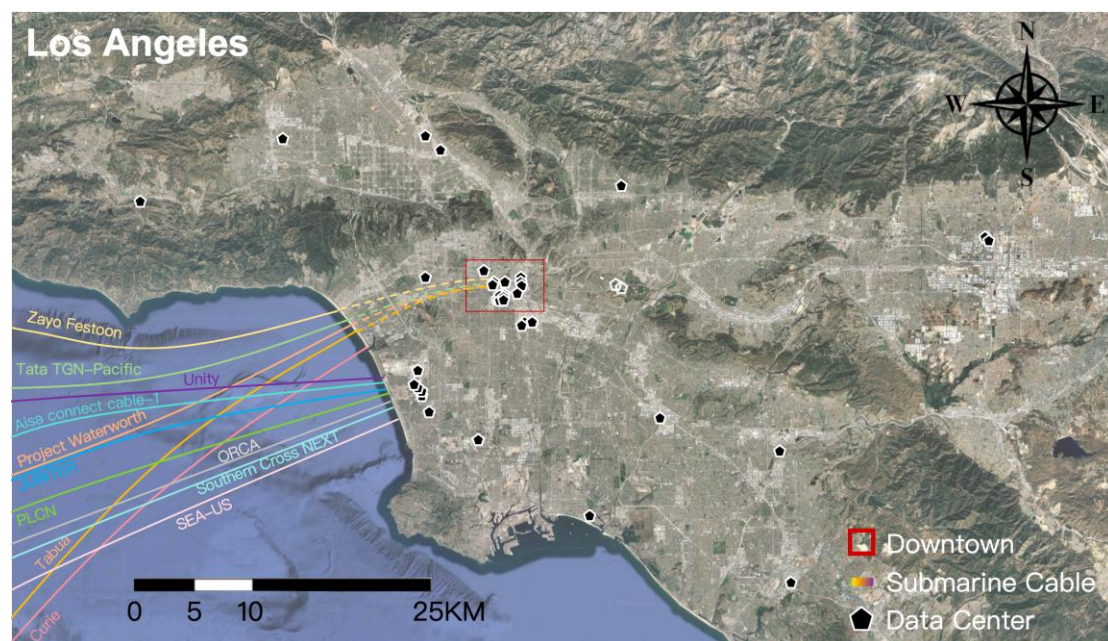


Fig.1|The distribution of data centers in Los Angeles metropolitan. There are 71 data centers in Los Angeles metropolitan area, California. The total power reaches 384 MW. Downtown LA (Red frame) is a concentrated area of data centers. Among them, the iconic One Wilshire Building is one of the most important network hubs on the West Coast and even in the United States. This 30-story building brings together more than 300 fiber optic lines. It is the landing point of many trans-Pacific submarine cables, connecting the Internet arteries of the United States and Asia, and carrying the traffic of Netflix, Amazon and other giants. At the same time, new data center clusters have emerged in El Segundo to the west (near Los Angeles International Airport) and Monterey Park to the east. The satellite is from Google Maps.

Results

Classification of different data center types

The impact of the Los Angeles data center has spatial heterogeneity. According to the different location, scale, architectural form and functional role within the urban fabric, this study divides the data centers in Los Angeles metropolitan into three types (Fig.2).

Residential mid-sized facilities are typically compact, low-to-mid-rise buildings embedded in or immediately adjacent to residential neighborhoods, often converted from existing commercial structures; these centers tend to provoke strong community concerns over noise, visual impacts, and quality of life, even as they offer modest tax revenue potential. In contrast, industrial hyperscale campuses consist of large, single-story developments located in suburban or exurban industrial zones, characterized by extensive land consumption, high-voltage grid connections, and heavy infrastructure footprints; such facilities are frequently sited in lower-density areas with abundant and affordable power, serving as major hubs for AI and cloud computing workloads with relatively limited direct residential opposition. Vertical colocation hubs, on the other hand, occupy multi-story structures within dense downtown office districts, leveraging strategic advantages such as proximity to dense fiber networks and trans-Pacific submarine cable landings; these facilities prioritize low-latency interconnection and network exchange functions over sheer horizontal scale, exemplified by iconic buildings like One Wilshire, which houses hundreds of fiber routes and serves as a primary internet gateway for the Pacific Coast.

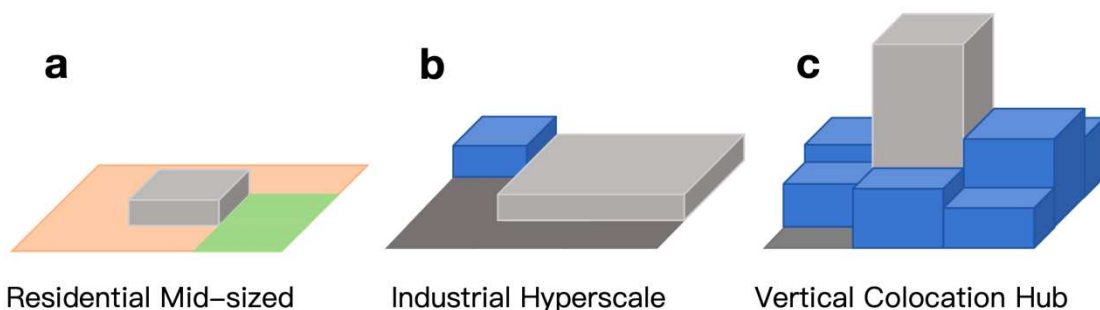


Fig.2|Three different data center models. **a** Facilities embedded in or adjacent to residential neighborhoods, typically 2~5 stories with limited footprint. Often adapted from existing commercial buildings. Example: Long Beach Data Center proposed project facing strong community opposition over noise, visual impacts, and environmental concerns despite significant tax revenue potential. **b** Large-scale, single-story campuses in suburban industrial zones, characterized by massive land consumption, high-voltage grid access, and heavy infrastructure footprints. Example: Vernon, an industrial city with fewer than 250 residents, emerging as a hub for AI-ready campuses due to cheap power and minimal residential opposition. **c** Multi-story facilities in downtown office towers, leveraging dense fiber connectivity and proximity to subsea cable landings. Optimized for low-latency interconnection rather than scale. Example: One Wilshire, a 30-story building housing over 300 fiber routes, serving as the Pacific Coast's primary internet exchange point.

NIMBY Conflicts, Housing price and Environmental Justice

To evaluate the environmental, social, and economic justice implications of residential mid-sized data centers, this study examines a set of community-level indicators including population density, minority population share, proportion of aged 17 younger and 65 older, income, unemployment, and poverty rates. These indicators are widely adopted in urban infrastructure and environmental justice research because they effectively capture social vulnerability, community resistance potential, and socioeconomic disparities that shape local responses to new developments^{39,43}. In the context of data centers embedded in or adjacent to residential neighborhoods, such metrics are particularly relevant for revealing how siting decisions may disproportionately affect vulnerable populations and exacerbate existing urban inequities^{40,56}.

The proportion of minority and poverty can evaluate the community social vulnerability, check whether the location of the data center is for those communities with more fragile social structures. This study selects the proportion of the population aged 17 younger and 65 older. Young and elderly people have weaker adaptability to environmental changes such as noise, heat emissions, and power infrastructure transformation brought by data centers and their ability to cope with emergencies, and they are more dependent on health and travel. Income is an important dimension to measure the economic and social status and resource access of the community. Low-income communities tend to have weak infrastructure and limited public service resources, and have poor ability to resist external shocks from external industries such as data centers, such as rising electricity prices. The employment rate reflects the economic vitality and labor stability of the community. In communities with high unemployment rate or low-skilled employment, social stability is relatively low, and the ability to withstand employment opportunities or potential negative effects brought about by industrial landing is different. Fig. 3 reveals distinct community profiles associated with residential mid-sized data centers in the Los Angeles metropolitan area.

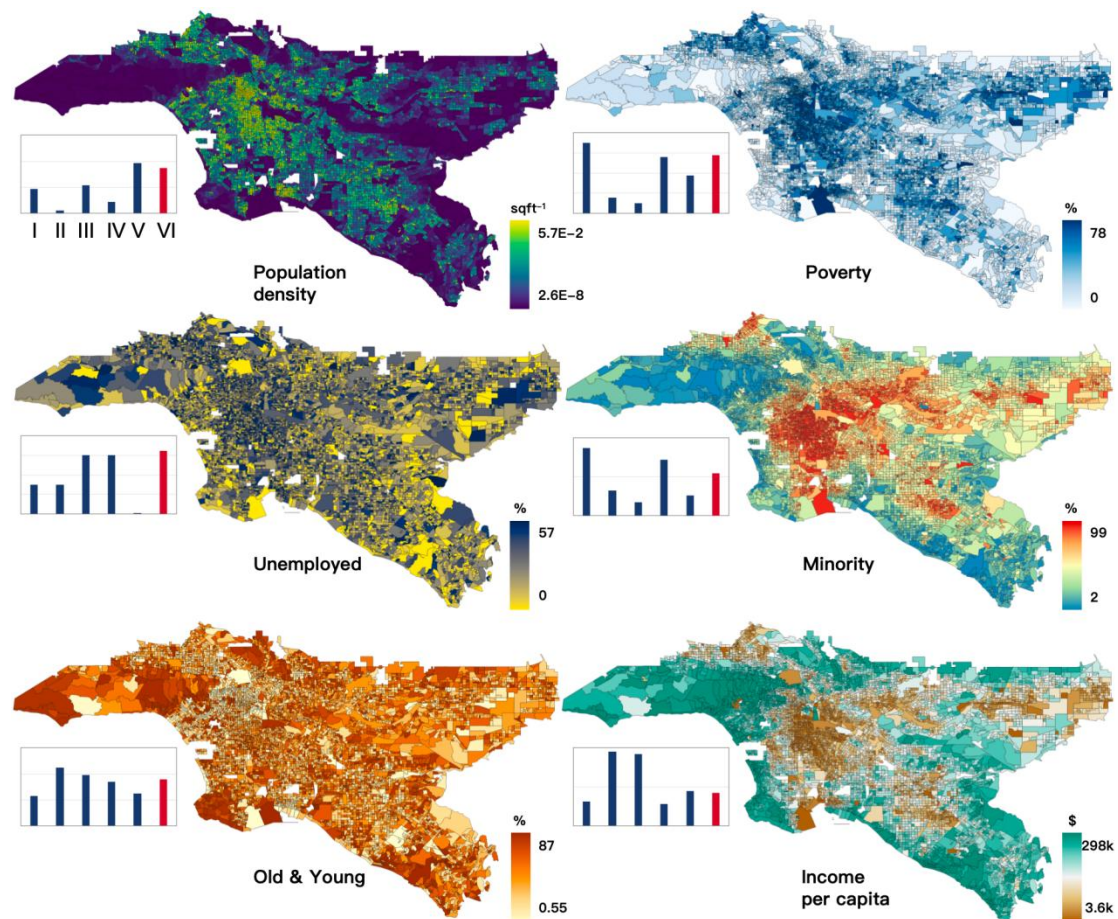


Fig.3|Parameters related to the communities and where type-a data center located. I. Cogent Data Center-La Mirada, at 16680 Valley View Avenue, 90638 La Mirada; **II.** Cogent Data Center-Pasadena, at 2947 Bradley Street, 91107 Pasadena; **III.** Converge Technology Solutions Agoura Hills, at 30077 Agoura Ct, 91301 Agoura Hills; **IV.** IHNNetworks Datacenter(SFV1), at 20339

Nordhoff Street, 91311 Chatsworth; V. Long Beach Data Center, at 3910 E 7th St., 90804 Long Beach; VI. is the average statistics in Los Angeles metropolitan.

The most of communities where data centers located are under the lower social vulnerability in Los Angeles metropolitan. According to the Next10 report, Data center developers tend to choose areas with complete infrastructure, land available and relatively friendly supervision. These communities often have an industrial and commercial foundation. Highly vulnerable communities often have stronger community organizations and environmental justice movements, and developers may take the initiative to avoid them to reduce protests and legal risks.

The data center can influence housing prices because of noise energy consumption and air pollution. This study selects the long beach data center which is in the central of the residential zone as the case study for housing prices and noise (Fig.4). The red brick computer room is a data centre transformed from an old industrial building. It was officially put into operation in 2012. The beige machine room is a standardised second-phase machine room newly built in the whole open space in the later stage. It was put into use in 2018. The construction period was 2017, with an initial IT power of 7.5MW, and the expansion to 11MW was completed in 2022. It fully includes the new construction project of civil construction, power distribution and refrigeration systems; the computer room is equipped with a large outdoor chiller unit (Fig.4a). There are 94 houses, 1 apartment and 8 commercial units in the price research zone (Fig.4b). The area and height of each architecture are showed in Fig.4c.

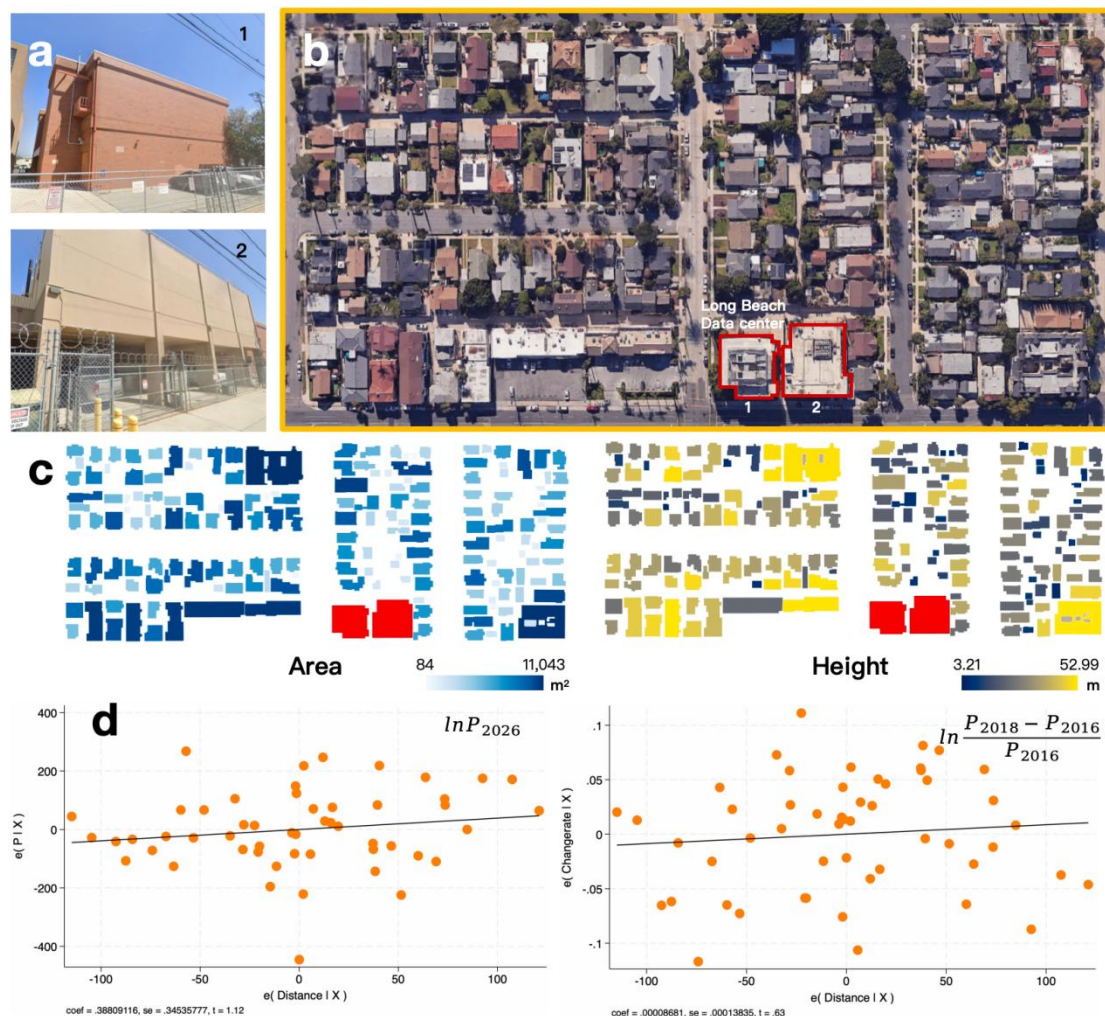


Fig.4|Housing price research around Long Beach data center. a Long beach data center is one of data centers that most closest to the residential zone covering an area of 1,225 m². It owns a red brick computer room and an expanded beige computer room. b demonstrates the price research

zone this study focuses. **c** The area and height of houses in this case study are ranging from 84-11,043 m² and 3.21-52.99 m relatively. **d** Partial scatter plot of residual 2026 housing price per sq-ft (logarithm) versus residual distance to the Long Beach data center, showing post-operation price-distance correlation. And partial scatter plot of pre-opening housing price growth rate (logarithm) against residual distance to the data center, serving as a pre-facility baseline benchmark.

In the residential price research area centered on the Long Beach data center, the residual value per square foot of housing prices in 2026 $e(P|X)$ and the partial correlation to the residual distance to the data center $e(\text{Distance}|X)$, other variables affecting house prices have been controlled (Fig.4d). The orange scatter distribution in the figure shows that after many years of operation of the data center, the residences close to the data center (the residual distance is a negative area) tend to have a lower price balance, while the price balance of houses that are far away are relatively high. The matching trend line has a slight forward slope (coefficient = 0.3881, standard error = 0.3453, $t = 1.12$), indicating that the farther away from the data center, the higher the residential price margin has an upward trend. This implies that data centers may have a negative impact on surrounding house prices through noise and air pollution, but the coefficient is statistically only at a significant marginal level, indicating that the impact intensity is moderate and there is some uncertainty, which may be partially offset by other community factors such as employment opportunities or location advantages.

This study also provides an important Pre-facility Baseline comparison, using the housing price growth rate ($P_{2018} - P_{2016}$) and residual from 2016-2018 (before the data center was put into use at the end of 2017) Scatter diagram of distance (Fig.4d). The trend line is close to the level, and the coefficient is close to 0, which is statistically not significant, indicating that the distance factor has no systematic impact on the growth rate of house prices before the operation of the data center. This benchmark comparison supports the potential causal relationship that the observed in Fig.4c may be related to the operation of the data center, reducing the risk of mixed deviations.

There are some residences disturbing by the noise from data center, some residents accept its existence, but strongly oppose noise and “industrial facilities entering residential areas”. As shown in Fig.5, the noise impact from data centers in El Segundo exhibits clear spatial heterogeneity. The Welcome Group project at 750 N. Nash Street (source noise $\approx 82\text{dB}$), which is replacing the former Hyatt Place hotel, will generate the most extensive disturbance zone among the five facilities, with potential annoyance radii reaching approximately 250 m during daytime and exceeding 1.2 km during summer nights. This aligns with the intense public opposition observed during the 2026 public hearings, where residents repeatedly highlighted concerns over continuous low-frequency noise from cooling systems and generators.

Among operational facilities, Serverfarm LAX1 at 444 North Nash Street ($\approx 85\text{dB}$) produces the largest affected area, while Spectrum Networks El Segundo ($\approx 78\text{dB}$) shows relatively limited impact. During nighttime and especially summer nights, when ambient noise levels drop and residents are more likely to have windows open, the red zones expand significantly, indicating that a considerable number of households in the surrounding residential areas are likely to experience sleep disturbance and reduced quality of life. These findings underscore the importance of incorporating site-specific noise modeling in the planning of data center developments near mixed-use zones.

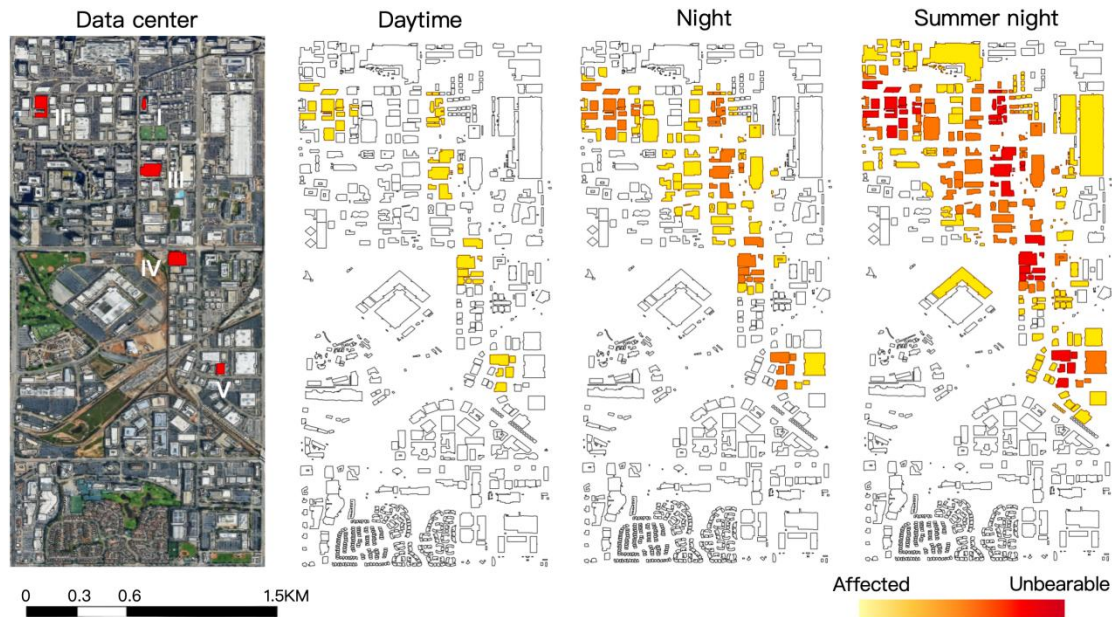


Fig.5|Noise tolerance radius in El Segundo. I. Welcome Group data center (The origin noise: 82dB, at 750 N. Nash St.) is under construction with fierce public protests because of the noise and energy consumption. **II.** Equinix LA3 (83dB, at 1920 E Maple Ave.). **III.** Serverfarm LAX1 (85dB, at 444 North Nash St.). **IV.** 2260 E El Segundo Blvd (LAX12) (80dB, at 2260 E El Segundo Blvd). **V.** Spectrum Networks El Segundo (78dB, at 2345 Alaska Ave.). In the daytime, night and summer night, the noise tolerance thresholds of citizens are 55dB, 50dB and 48dB relatively. Citizens living in red area are probably disturbed by data centers.

Urban Heat Island Effect and Capitalization

Data center can cause urban heat island effect, relative references mainly focused on high-density cities or some specific climate such as Silicon Valley and Phoenix. Except for Downtown CBD, the Los Angeles metropolitan area is a typical low-density urban sprawl, with low building density, relatively large greenery and open space, and good heat diffusion conditions. The heat emissions of a single data center are relatively scattered and will not form a strong local heat island like high-density CBD.

This study focuses on the heat island effect and diffusion characteristics of the vertical Colocation Hub in downtown Los Angeles. Unlike low-density urban expansion areas, Downtown LA concentrates a number of high-density vertical data centers or telecommunications facilities such as One Wilshire, Aon Center, Telecom Center LA, etc. (Fig.6a, Fig.6c). Take the cluster composed of facilities such as CoreSite LA1, Crown Castle LA1, DataBank LAX1, InfoRelay, Colocation America LA1 and US Colo as an example, its total power is about 48 MW, which produces a significant local heat island effect in a high-density environment in the city center. Among them, the radius of the +2°C hot island is about 0.46 km, the radius of the +1°C hot island is about 1.38 km, and the radius of the +0.5°C hot island extends to 2.31 km (Fig.6b). Due to the large height of the building (Fig.6d), these facilities not only enhance the intensity of the heat island effect, but also promote the vertical diffusion of heat. This study quantitatively depicts the spatial impact range of the heat island: the intensity and radius of the heat island mainly depend on factors such as the total power capacity (MW), building height, land area, local climatic conditions and greening rate of the facility (Fig.6e).

This finding shows that in high-density CBD areas, waste heat emissions from data center ai infrastructure are more likely to form a strong local heat island effect and achieve a certain degree of vertical diffusion through building heights. Compared with that, it is usually difficult for single facilities to form a significant local heat island due to low building density, large green space and good heat diffusion conditions in other low-density “big cake” areas of Los Angeles.

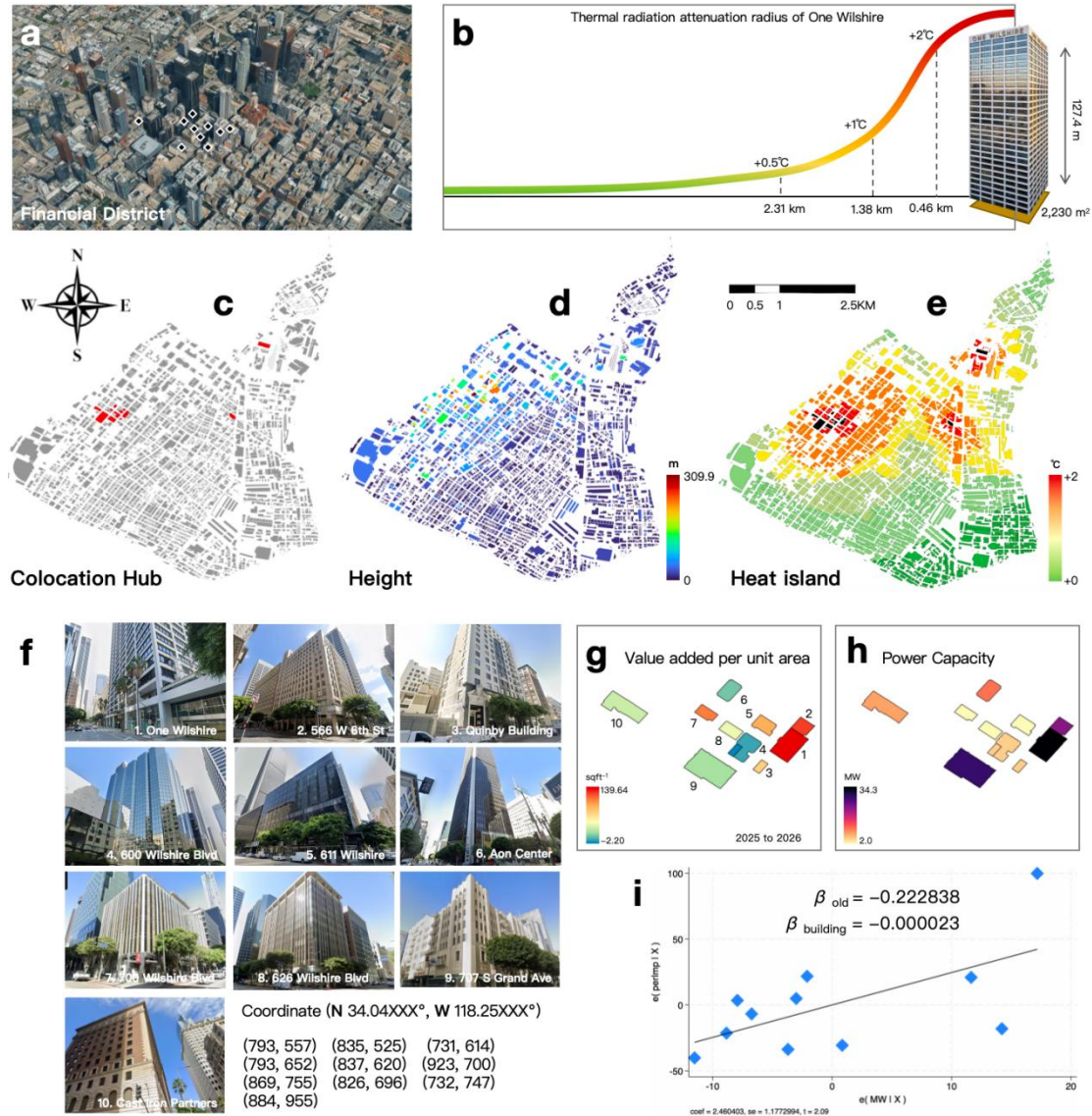


Fig.6|Colocation hub heat island and commercial value-added in downtown. The financial district concentrated One Wilshire and so on with power capacity approximately 130MW in sum (a). The radius of +2°C, +1°C and +0.5°C heat islands caused by One Wilshire are 0.46km, 1.38km and 2.31km relatively (b). There are vertical colocation hubs concentrated in downtown such as One Wilshire, Aon Center, Telecom Center LA (c). The height of the building will increase the intensity of the heat island and the height of vertical diffusion (d). The colocation hub will produce a heat island effect, raising the temperature of the surrounding area. The radius of the heat island is determined by the total force power (MW), relative building height (m), area (m²), street direction, climate and greening rate (%) of the colocation hub (e). 10 colocation hub buildings in downtown with their coordinates (f). The value improvements per area from 2025 to 2026 are showed in (g) ranging from -2.20 \$/sqft to 139.64 \$/sqft. The power capacity of each colocation hub buildings is illustrated in (h) ranging from 2.0 MW to 34.3 MW. The partial regression parameter of power capacity is approximately 2.46, t = 2.09, the positive correlation is obvious; age and total area of building are as control variables and their parameters are approximately -2.2E-1 and -2.3E-5 (i).

Energy Consumption and Carbon Emissions

Data centers consume much energy in both construction and use period generating air pollutants. The energy and carbon emission balance of data centers in Los Angeles metropolitan are showed in (Fig.7). According to relative research, a 10 MW data center can cause approximately

1,000~2,000 metric tons of CO₂ by using concrete and 950~1,900 metric tons of CO₂ by using structural steel. In total, it will generate 2,550~5,500 metric tons of CO₂, 8~30 metric tons of NO_x, 0.5~3.0 metric tons of PM and 1.5~6.5 metric tons of CO during construction. A 10 MW data center running continuously consumes roughly 87,600 MWh annually, this equates to approximately 37,668 metric tons of CO₂ emissions per year from electricity alone. A large data center cooling system containing approximately 1,000 kg of R-410A could annually leak between 20 and 50 kg, equating to about 42~104 metric tons of CO₂-equivalent emissions^{2,60}. So each 1MW power data center will cause approximately 3,777 tons CO₂ each year. However, according to the GHG-Protocol standard generally used in the United States, the average PUE is 1.32 and the average emission factor eGRID is 0.371kg CO₂/kWh, so the average carbon emission in general is 4,295 tons CO₂ per 1MW each year. This is because the newly hyper-scale data centers using water-cooling system can get the PUE down to approximately 1.16, this study adapts the mean value, which is approximately 4,036 tons CO₂.

Definitely, the energy consumption and carbon emission cause a huge pressure on power system and green space in Los Angeles metropolitan (Fig.7a). The power capacity in each community is ranging from 0.044MW to 3,741MW. According to the capacity factors of each energy and the proportion of renewable energy (Fig.7b), they generate about 12,620GWh yearly but the renewable energy is in low proportion against what the builder of data center claimed; the green space is ranging from 0.03 acres to 81million acres, according to the carbonisation and tree crown area of different type of plants (Fig.7c), they can fix about 176,428,901 t CO₂ per year.

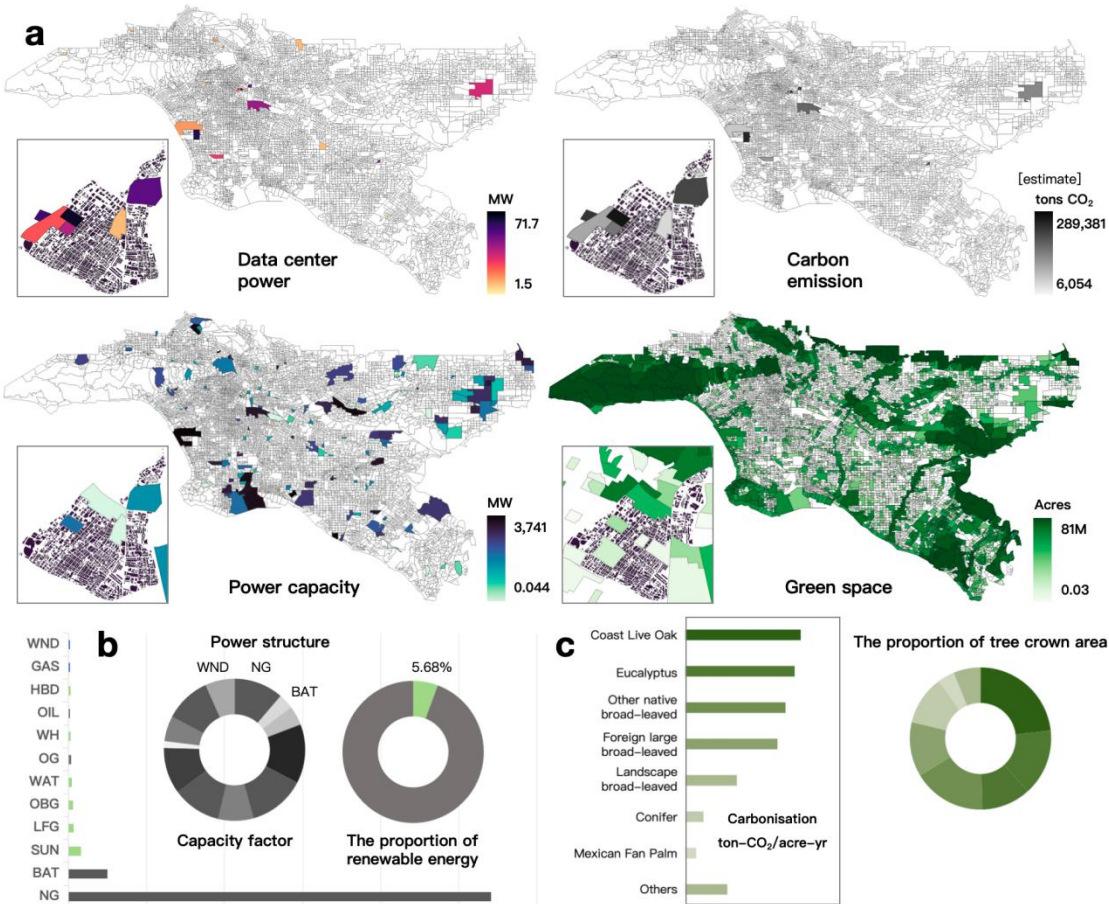


Fig.7|Energy and carbon emission justice. Power capacity of Data centers in each street is difference ranging from 0 to 71.7MW; The power capacity in Los Angeles metropolitan is mainly generated by Vernon, El Segundo, Ontario and Long beach harbor ranging from 0.044MW to 3,741MW with totally 12,620GWh in 2026; Data centers will also generate much carbon emission, in estimation, approximately 1,549,824 tons CO₂ in 2026; Green space such as forest, park and cityscape is covered about 108,297,820 acres area, about 1.28% in this case study, it is significant as its carbonisation (a). The main three power generation methods are natural gas (85.81%), natural gas with best available techniques (7.92%) and solar (2.58%). Capacity factor is the radio

of power generation and the capacity which characterizes the utilization efficiency. The proportion of renewable energy including solar, landfill gas, other biomass gas, hydro-power and wind is 5.68% (b). In Los Angeles metropolitan, coast live oak have the strongest carbonisation ability, about 4.94 t-CO₂/acre-yr with 23.2% of tree crown area. In the following order are eucalyptus (4.68 t-CO₂/acre-yr, 15.1%), other large broad-leaved (3.95~4.29 t-CO₂/acre-yr, 28.0%), conifer (0.78 t-CO₂/acre-yr, 11.2%), fan palm (0.47 t-CO₂/acre-yr, 3.9%) and others like sage-scrub (0.95 t-CO₂/acre-yr, NA). So the case study can absorb approximately 176,428,901 t-CO₂/yr.

Discussion

Our results demonstrate markedly different environmental-social-economic outcomes across three data-center typologies within the Los-Angeles metropolitan area. The huge urban infrastructure will shape the spatial distribution of cities by making the differentiation on environment burden and economic benefits⁴⁴. Industrial-hyperscale and vertical-colocation hubs impose heavy energy-consumption, carbon-emission and heat-island risks, with our sampled facilities (384 MW installed capacity) consuming 3364 GWh electricity and emitting roughly 1,549,824 tons of CO₂ per year and the One Wilshire hub driving localized temperature rise, while residential-mid-sized data-centers generate negligible heat-island stress but trigger prominent noise-related conflicts within 162 m-565 m depending on time periods; our hedonic-pricing model further confirms that the positive correlation between data-center distance and housing prices in Long-Beach lacks statistical significance ($\beta=0.3881$, $t=1.12$), and only residential-type data-centers noticeably affect housing values whereas all three types deliver benefits including digital-industry agglomeration and increased tax revenue, which proves that a unified assessment standard would produce biased evaluation results for data-centers of different forms.

Against the backdrop of global digital-transition and urban-sustainability research, this study makes two key theoretical advances: unlike prior studies that separately examined carbon emission, heat-island effects or housing-price-related NIMBY impacts, we construct a typology-adaptive data center sustainability index (**DCSI**) integrating environmental, social, economic dimensions, screen valid indicators according to surrounding built-up conditions and separately apply the entropy-weight method for each data-center type to avoid calculation errors from inapplicable indicators²⁰; more importantly, even though parameter calibration relies on Los Angeles-derived noise-attenuation, heat-decay and hedonic-pricing results, our framework is not limited to this single-city case and can be applied globally by substituting local-climate, urban-morphology and socioeconomic parameters, shifting existing research from case-specific analysis to generalized assessment and providing empirical support for SDG 11 and SDG 13.

Our outcomes provide targeted planning suggestions for Los Angeles metropolitan and generalized policy references for worldwide cities. Local administrators in Los Angeles should require industrial-hyperscale data centers to deploy photovoltaic systems to reduce grid-dependent carbon emissions, optimize street ventilation and green-space layout around downtown vertical hubs to relieve heat-island problems, and set reasonable noise-buffer zones for residential-mid-sized data centers rather than completely banning their construction given the insignificant housing price effect in Long Beach; for global metropolitan areas, urban planners should first classify local data-centers into our three proposed categories instead of adopting one-size-fits-all restrictive policies, control total installed capacity of data centers in regions short of green-energy supply, and improve heat-dissipation and sound-insulation design for downtown vertical facilities, with our **DCSI** index serving as a pre-evaluation tool to balance digital-economy dividends and urban livability before new-project approval.

This research still has several notable limitations that can be addressed in follow-up studies. Although our **DCSI** framework possesses global transferability, heat-attenuation and noise-attenuation coefficients are calibrated only by Los Angeles datasets; future research can incorporate samples from Europe, East-Asia and Southeast-Asia to recalibrate model parameters and conduct cross-city comparisons of **DCSI** scores to analyse how climate conditions and urban density affect comprehensive influences of data-centers, expand our indicator system by adding edge-computing-oriented distributed data centers, adopt long-term time-series satellite and socioeconomic panel data to explore dynamic changes of sustainability performance, and further distinguish fossil-fuel-powered and green-energy-powered data centers to refine environmental dimension indicators for more-accurate assessment.

Methods

Standardise

Various social indicators (population density, poverty rate, unemployment rate, ethnic minority proportion, age structure, per capita income) are inconsistent, so Min-Max is standardised, the numerical value is compressed to the 0-1 range, and horizontal comparison is achieved, corresponding to the relative height of the column in the figure.

$$Z_{jk} = \frac{X_{jk} - X_{min}}{X_{max} - X_{min}} \quad (1)$$

j : six data center residential communities ($j = \text{I, II, III, IV, V, VI}$);

k : six social economic indicators;

X_{jk} : The k original observation value of the community where the j data center is located;

X_{min} and X_{max} : The minimum and maximum values of this indicator in 6 samples;

Z_{jk} : After standardisation, the value, that is, displayed in the bar chart.

Hedonic Pricing Model

We adopt the Hedonic-price model^{72,75} to quantify how proximity to data-centers reshapes residential housing prices across the Los-Angeles metropolitan area. Two regression specifications are constructed for different analytical purposes.

$$\ln P_{2026i} = \alpha + \beta_1 \text{Dist}_i + \beta_{2\sim 5} \mathbb{X}_i + \varepsilon_i \quad (2)$$

where P_{2026i} represents the unit housing price of property i in 2026; Dist_i is the Euclidean distance from house i to the nearest data-center; $\mathbb{X}_i$ is a set of control variables including building age, floor area, bed and bathroom, and garden; α is the intercept term, β_1 and $\beta_{2\sim 5}$ denote regression coefficients; ε_i is the random error term. The coefficient β_1 reflects the overall influence of data-centers on present-day housing prices.

The second difference-in-form version isolates long-term price-change effects by eliminating time-invariant housing attributes:

$$\ln\left(\frac{P_{2018} - P_{2016}}{P_{2016}}\right)_i = \alpha + \beta_1 \text{Dist}_i + \beta_{2\sim 5} \mathbb{X}_i + \varepsilon_i \quad (3)$$

Here $\ln\left(\frac{P_{2018} - P_{2016}}{P_{2016}}\right)_i$ is the logarithmic housing-price growth rate between 2016 and 2018, which captures whether data-center construction triggers continuous appreciation or depreciation of surrounding real-estate values.

Noise logarithmic attenuation model

We calculate the spatial attenuation of noise generated by data-centers with a logarithmic-distance decay formula widely adopted in environmental acoustics research⁷⁴:

$$L(d) = L_0 - 10\lg\left(\frac{d}{d_0}\right) - \alpha(d - d_0) - \Delta L_{ground} \quad (4)$$

Where L_0 is the reference noise level measured at the reference distance d_0 from cooling-equipment outlets; $L(d)$ represents noise intensity at distance d ; $10\lg(d/d_0)$ accounts for geometric divergence of sound waves; α is the atmospheric-absorption coefficient varying with temperature and humidity for daytime, nighttime and summer-night scenarios; ΔL_{ground} refers to ground-surface attenuation caused by vegetation and buildings. By setting the threshold of resident-disturbing noise, we calculate critical impact radii of 162 m (daytime), 248 m (nighttime), and 565 m (summer nights) in the El-Segundo area. The calculated noise-affected area relative to total urban built-up area forms the original dataset for the S_1 (noise-invasion) indicator in our **DCSI** evaluation system.

Data center heat island attenuation estimation

We firstly establish a multiple-regression-based surface-temperature-prediction equation to quantify heat emission from vertical colocation hubs⁷¹:

$$\Delta T = 0.0004 \times S + 0.02 \times H - 0.006 \times E - 1.2 \times NDVI \quad (5)$$

In this formula, ΔT is the temperature increment induced by data-center waste-heat; S is the installed power of the data-center; H stands for building height; E represents street orientation; $NDVI$ is the normalized difference vegetation index. This equation explains how building morphology and vegetation jointly determine near-field warming intensity around facilities such as the One Wilshire building. We further apply an exponential decay function to describe heat reduction with increasing distance.

According to $\Delta T_r = \Delta T_0 \cdot e^{-kr}$, where ΔT_0 is the temperature rise at the building boundary; ΔT_r is temperature increment at distance r ; k is the heat-attenuation coefficient determined by local urban canyon conditions. Rearranging this formula yields the calculation of influence radius:

$$r = -\frac{1}{k} \ln\left(\frac{\Delta T_r}{\Delta T_0}\right) \quad (6)$$

We set threshold warming values of 2°C, 1°C and 0.5°C and calculate corresponding influence radii of 0.46 km, 1.38 km and 2.31 km. To adapt this model for global-scale application, we introduce a regional correction coefficient q_{LA} calibrated by Los-Angeles urban-climate conditions to obtain adjusted effective heat-impact radius:

$$r_{adjusted} = q_{LA} \times r \quad (7)$$

The final adjusted heating-impact area is used for computing E_3 (local heat-island coercion), one of the core environmental-dimension indicators of the **DCSI** model.

Evaluation of energy consumption

We quantify annual electricity consumption of sampled data-centers using the widely-adopted power-calculation formula for computing infrastructure:

$$Annual\ Electricity = \frac{Installed\ Capacity \times 8760 \times Capacity\ Factor}{1000} \quad (8)$$

Where *Installed Capacity* is total rated power of our investigated data-centers (384 MW in this Los-Angeles case); 8760 stands for total hours within one full year; *Capacity Factor* (CF) represents the operational load rate. Given that IT servers and cooling equipment run 24 h per day throughout the whole year, we set CF=0.998 for data-center facilities; Dividing by 1000 converts the unit from MWh to GWh.

Evaluation of vegetation carbonisation capacity

Within Los-Angeles metropolitan area, the per-acre-land carbon-sequestration rate for each tree species is determined by the canopy-area fraction, regional canopy coverage coefficient and species-specific sequestration rate⁷³.

$$\begin{cases} T_i = C_i \cdot f \cdot S_i \\ [4pt] f = \frac{A_{canopy, total}}{A_{total}} \\ [4pt] Total_CO_2 = A_{total} \sum_{i=1}^n T_i \end{cases} \quad (9)$$

Where:

T_i = species-specific carbon sequestration per acre of green-land ($t\ CO_2 \cdot acre^{-1} \cdot yr^{-1}$);

C_i = proportion of canopy area of species i in total tree-canopy area;

f = ratio between total canopy area and total green-space land area;

S_i = carbon-sequestration rate per canopy area for species i ($t\ CO_2 \cdot acre^{-1} \cdot yr^{-1}$);

A_{total} = total green-space area (acre).

Under consistent regional-climate conditions and mature-tree status, f and S_i are constant, which yields $T_i \propto C_i$. It demonstrates that the per-land-area carbon-sequestration capacity is positively correlated with canopy-area proportion.

All outputs derived from the above-mentioned Hedonic-pricing, noise-attenuation and thermal-decay models serve as raw inputs for our typology-adaptive **DCSI** framework. Parameters calibrated from Los-Angeles observations can be generalized to other global cities when local urban-form, meteorological and socioeconomic data are available, which ensures that our evaluation system is not limited to the Los-Angeles case-study context.

Data Center Sustainability Index

We established a typology-adaptive evaluation framework for the Data-Center Sustainability Index (**DCSI**) covering environmental (**E**), social (**S**), and economic (**Ec**) dimensions, instead of applying a fixed set of indicators for all data-center forms indiscriminately. We screened valid evaluation indicators according to the operating characteristics and surrounding built-up environments of each data-center type (Table 1).

For residential mid-sized data-centers, smaller equipment size and scattered heat discharge make localized heat-island effects negligible, so we mark E_3 as N.A. Meanwhile, these facilities are adjacent to residential neighbourhoods, hence noise invasion (S_1) and spatial conflict (S_2), together with housing-price-related benefits (Ec_1), exert obvious local impacts and are retained for calculation. Industrial hyperscale data-centers are purposely sited in industrial districts far from residential communities. Even with huge heat-release and carbon-emission pressure, they barely trigger resident-related noise complaints or land-use conflicts. Therefore, S_1 and S_2 are excluded, while energy-carbon and economic-gain indicators remain valid. Vertical colocation hubs are embedded inside high-rise downtown buildings with reinforced sound-insulation designs. Building envelopes block most equipment-generated noise from spreading outward, and surrounding land-use is dominated by offices rather than housing. For this reason, noise invasion (S_1), residential spatial conflict (S_2) and residential-property appreciation (Ec_1) are labelled N.A., whereas heat-island risks and digital-economy-related advantages become prominent.

Table 1 Indicator system for the data center sustainability index (*DCSI*)

		Residential	Industrial	Vertical		
<i>E</i>	<i>E₁</i>	Energy consumption intensity	N.A.			
	<i>E₂</i>	Carbon emission coercion				
	<i>E₃</i>	Local heat island coercion				
<i>S</i>	<i>S₁</i>	Noise invasion			N.A.	N.A.
	<i>S₂</i>	Spatial conflict			N.A.	N.A.
<i>Ec</i>	<i>Ec₁</i>	Real estate value-added				N.A.
<i>DCSI</i>	Data center sustainability Index					

556 All retained raw indicators are standardized to a range from 0 to 1 using the min-max method.
 557 We apply the entropy-weight method separately for each type rather than adopting universal fixed
 558 weights. This approach avoids weight bias induced by including non-applicable items, and makes
 559 our evaluation framework adaptable globally. After calibrating attenuation coefficients of heat,
 560 noise and hedonic-price parameters based on the Los-Angeles metropolitan dataset, this *DCSI*
 561 framework can be deployed in other global cities, as long as researchers classify local data-centers
 562 into the three typologies and collect corresponding accessible variables. The final *DCSI* score falls
 563 between 0-1, where higher values indicate worse sustainability performance and stronger
 564 urban-scale burdens brought by data-center deployment.

565

$$DCSI = \sum_{j \in \text{valid}} \omega \times Z_{ij}^{norm} \quad (10)$$

566

567 Data Availability

568 The underlying dataset including housing-price records, detailed power-allocation files and
 569 site-specific operational parameters of data-centers is confidential owing to privacy protection and
 570 commercial-security restrictions from local government and data-center operators, which are not
 571 publicly accessible. Derived processed results, normalized indicator values and calculated DCSI
 572 scores that support the findings of this study are available from the corresponding author upon
 573 reasonable request with approved non-commercial research agreements. The publicly accessible
 574 datasets including NDVI and urban-land-use products we used can be downloaded from the
 575 United States Geological Survey (USGS) platform.

576

577 References

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Competing Interests

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.