



Data-Driven Methods for Building Solar Potential Evaluation: A Review Across Rooftops and Facades

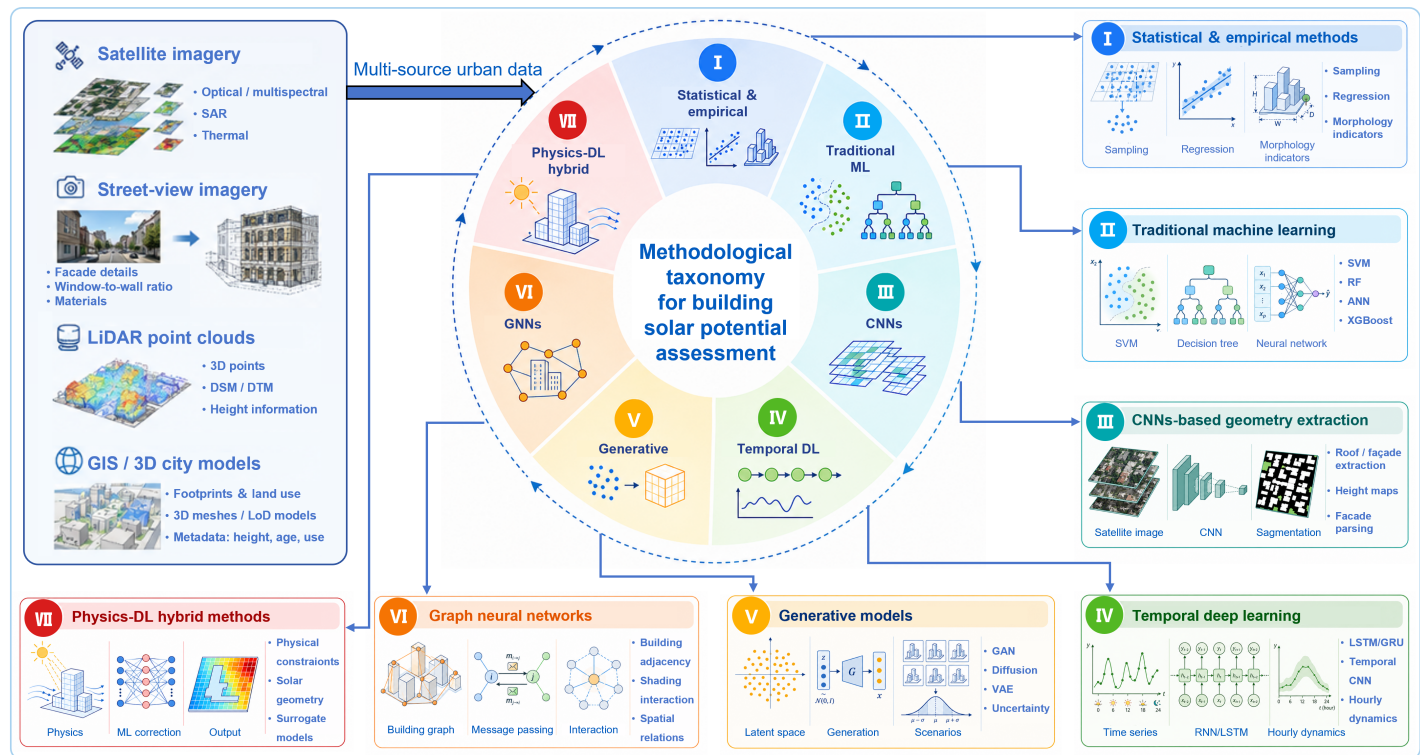
Haoshan Ren,^{1,2} Zhisheng Huang,¹ Junyi Yang,¹ Natasa Nord,² Yongjun Sun,³ and Yafeng Gao^{4,*}

*Correspondence: gaoyafeng79@cqu.edu.cn

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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Building solar potential assessment has evolved from statistical models to physics-deep learning hybrids.
- Facades offer solar potential comparable to rooftops but remain significantly understudied.
- Several studies achieved either large spatial scale or good temporal/spatial detail, but rarely all simultaneously.
- Validation data, benchmark datasets, and scalable high-resolution methods remain critical gaps.



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Haoshan Ren,^{1,2} Zhisheng Huang,¹ Junyi Yang,¹ Natasa Nord,² Yongjun Sun,³ and Yafeng Gao^{4,*}

¹State Key Laboratory of Subtropical Building and Urban Science, School of Architecture, South China University of Technology, Guangzhou 510641, China

²Energy and Process Engineering, Norwegian University of Science and Technology (NTNU), Trondheim NO-7491, Norway

³Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong SAR, China

⁴Chongqing University, Joint International Research Laboratory of Green Building and Built Environment, Ministry of Education, Chongqing 400044, China

*Correspondence: gaoyafeng79@cqu.edu.cn

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INTRODUCTION

The building sector accounts for approximately 30% of global final energy use, over 50% of global electricity demand, and roughly 40% of energy-related CO₂ emissions.^{1,2} Urban areas, which house over 55% of the world's population, are responsible for up to 87% of global energy use and approximately 70% of energy-sector CO₂ emissions.^{3,4} With the urban population projected to reach 68% by 2050 and building floor area expected to double by 2060,^{3,5} urban building energy demand is projected to rise from approximately 15,833 to 23,333 TWh per year, and building-related electricity demand could reach approximately 65,000 TWh per year.⁶ In response, governments have established ambitious decarbonization targets, including the European Union's Solar Rooftop Initiative mandating PV installation on new and renovated buildings, and China's dual-carbon targets aiming to peak emissions before 2030 and achieve carbon neutrality by 2060.⁷ Meeting these targets requires a large-scale expansion of building solar capacity.

Distributed photovoltaic (PV) systems on building envelopes, primarily rooftops and facades, represent a promising approach to urban energy challenges. Unlike ground-mount utility-scale PV, building-integrated and building-attached PV makes use of existing surfaces to generate electricity on-site, reducing transmission losses, alleviating pressure on urban grids during peak demand, and enabling building owners to participate directly in the energy transition.^{7,8} Rooftop PV alone could supply approximately 28% of national electricity use in Switzerland,⁹ more than 40% when accounting for hourly supply-demand matching,¹⁰ and the entire electricity demand of the European Union under the EU Solar Rooftop Initiative.¹¹ Including facades further increases potential. A study of over 170,000 buildings in Beijing found that facade PV potential was equivalent to 239% of rooftop potential,¹² and a global evaluation of 120 cities reported facade PV potential averaging 68.2% of rooftop potential.¹³ The total building envelope, rooftops, and facades together represent a vast and largely untapped solar resource.

However, accurately evaluating the solar potential of building surfaces is challenging due to the complexity of the urban built environment. Buildings exhibit diverse geometric forms: roofs vary in shape, slope, and orientation, while facades incorporate windows, balconies, shading devices, and materials with widely differing optical properties.^{14,15} In dense urban settings, buildings cast shadows on neighboring surfaces, reflect solar radiation, and restrict sky visibility.^{16,17} The complex urban morphology could substantially reduce building solar potential in high-density districts, for rooftops and facades.^{18,19} Solar potential can therefore vary dramatically between buildings meters apart, making generalized estimates unreliable. Accurate, building-specific evaluation is essential for PV system design, municipal energy

planning, grid infrastructure planning, and evidence-based renewable energy policy.^{20,21}

Physical simulation methods can model these effects with high fidelity. Tools such as Radiance,²² Ladybug Tools,²³ and CitySim²⁴ compute solar irradiance on building surfaces by simulating the physical transport of solar radiation through the urban environment, accounting for beam, diffuse, and reflected radiation components. These physics-based approaches are well-established and have been validated against measured irradiance data.^{16,25} However, their computational cost is substantial: ray tracing for a single building envelope can require hours of computation depending on geometric complexity and temporal granularity.²⁶ The burden becomes prohibitive for routine evaluation at a city scale. Jakubiec and Reinhart²⁷ reported that simulating over 17,000 buildings required 5 to 180 minutes per building using Radiance and DAYSIM. Desthieux et al.²⁸ estimated approximately 900 hours to compute hourly irradiance for 300 km² in Geneva, and Zhuang et al.²⁹ confirmed that existing methods become computationally prohibitive at scale. This bottleneck has motivated the search for faster alternatives that preserve acceptable accuracy while dramatically reducing computation time.

Beyond computing irradiance on known surfaces, there is an equally important prior problem: identifying building surface areas that are actually available for PV installation. Rooftops contain superstructures such as chimneys, HVAC equipment, and elevator penthouses that occupy space and cast additional shadows. Boccalatte and Chanussot³⁰ reported that excluding roof superstructures reduced solar potential by an average of 43% across approximately 35,000 buildings in Geneva, ranging from 31% in suburban areas to 51% in urban centers. A study from Saudi Arabia reported only 28% of rooftop area as usable for PV due to parapets, water tanks, and air conditioning equipment.³¹ Facades present greater challenges: windows, balconies, and heterogeneous cladding materials mean only a fraction of the vertical surface is suitable for PV mounting.³² Traditionally, obtaining this information at the city scale required labor-intensive manual surveys or detailed 3D building models unavailable for most of the world's cities.³³ The dual challenge of predicting irradiance accurately and determining usable surface area precisely, both at scale, defines the core challenge that data-driven methods aim to address.

Data-driven methods based on machine learning (ML) and deep learning (DL) have emerged as a powerful paradigm for building solar potential evaluation at large spatial scales. Unlike physical simulation, which encodes explicit physical equations, data-driven methods learn the relationship between inputs and solar potential (or components) directly from data.^{34,35} This approach offers three advantages. First, ML and DL models can serve

Table 1. Data sources used in data-driven building solar potential evaluation.

Data type	Information provided	Spatial resolution	Key studies
Optical satellite imagery	Building/rooftop footprints, land cover, larger superstructures (at fine resolution)	0.3 to 10 m	[37,38,43,44]
Aerial imagery	Roof geometry, superstructure detail	0.05 to 0.5 m	[61–63]
Airborne LiDAR	3D point clouds, DSM/DTM, roof slope and aspect	0.1 to 1 m (1–20 pts/m ²)	[10,33,42]
Street-level imagery (Google Street View, Baidu, panoramic)	Facade details, window-to-wall ratio, material type	cm-level	[14,32,64]
3D city models and GIS (LoD1 to LoD3)	Building footprints, height, morphology parameters	Building-level	[9,12,18,20,21]
Meteorological and solar radiation data	Irradiance, temperature, cloud cover (stations, satellite-derived, reanalysis)	point to 30 km, hourly	[9,10,34]

as fast surrogates for physics-based simulation, achieving high accuracy while reducing computation time.^{15,36} Second, DL-based computer vision can automatically extract building geometry, including roof outlines, superstructures, and facade features, from widely available remote sensing imagery and street-level imagery, alleviating the dependency on expensive LiDAR data or manual surveys.^{37,38} Third, data-driven methods capture nonlinear relationships between urban morphology and solar potential that are difficult to express in closed-form equations, enabling rapid evaluation from a limited set of morphological indicators.^{39,40} The past decade has witnessed a rapid expansion of this research field. Early work employed statistical sampling and regression on GIS (Geographic Information System) and land-use data.^{41,42} Traditional ML algorithms, e.g., support vector machines (SVM), random forests (RF), and artificial neural networks (ANN), enabled national-scale building-level PV potential evaluations.^{9,10} Convolutional neural networks (CNNs) automate rooftop extraction from satellite imagery.^{43,44} Generative adversarial networks (GANs) have been applied to synthesize training data and stochastic irradiance fields,^{45,46} graph neural networks (GNNs) have been employed to model inter-building shading and reflection,⁴⁷ and vision transformer-based foundation models have demonstrated zero-shot segmentation for emerging cities with limited local data.⁴⁸

Several review studies have examined aspects of this rapidly growing field. Tian et al.⁴⁹ reviewed ML and DL methods for solar radiation and PV power forecasting in urban environments from a multi-scale perspective. Wang and Xiang⁵⁰ reviewed ML techniques for power forecasting in building-integrated and building-attached PV systems. Irmak Koker et al.⁵¹ provided a systematic review of solar irradiance modeling on building facades, identifying four key challenges related to simplified radiation paths, uniform albedo assumptions, spatiotemporal granularity trade-offs, and computational constraints. Yang et al.⁵² reviewed methods for modeling spectral solar irradiance and explored opportunities for ML applications. These reviews have made valuable contributions, yet none has covered the complete methodological pipeline from the extraction of building geometry through estimation of solar irradiance to final evaluation of PV potential for both rooftops and facades. Furthermore, the existing reviews were published before the recent emergence of generative models, GNNs, and foundation models as tools for building solar evaluation, and therefore do not reflect the most current methodological frontier. The present review addresses these gaps by systematically examining the full data-driven pipeline across both rooftops and facades, tracing the methodological progression from statistical methods through traditional ML and CNNs to the most recent generative, graph-based, and physics-DL hybrid approaches. The review also includes a cross-cutting analysis of urban morphology as a predictor of solar potential and examines how spatial and temporal granularity have evolved across the methodological generations.

The remainder of this paper is organized as follows. Section 2 provides background on the fundamentals of building solar potential and the data sources that support data-driven methods. Section 3 presents the methodological review, organized into seven groups of increasing model complexity, spatial and temporal granularity, and physical detail, and concludes with a synthesis of the methodological progression along the dimensions of spatiotemporal granularity, physical modeling detail, and building surface coverage. Section 4 examines emerging data-driven paradigms and cross-cutting themes. Section 5 identifies remaining gaps in the literature and outlines directions for future research. Section 6 concludes the paper with a

synthesis of the state of the art and unresolved challenges.

BACKGROUND ON BUILDING SOLAR POTENTIAL AND DATA

Building solar potential

Building solar potential refers to the amount of solar energy that can be harvested from a building's envelope surfaces and converted into usable energy forms, most commonly electricity through photovoltaic (PV) modules. Solar thermal collection is an alternative pathway for utilizing building solar energy but falls outside the scope of this review, which focuses on PV-based electricity generation. Building solar potential can be structured as a hierarchy of successive levels, each introducing additional constraints that bring the evaluated potential closer to real-world achievable values.⁴¹ The first level, geographic potential, represents the total annual solar irradiance received by all building surfaces in a given location, determined by latitude, climate, and the three-dimensional geometry of the buildings. The second level, physical potential, constrains the geographic potential by the surface area that is practically available for PV module installation, accounting for roof superstructures, facade openings, inter-building shading, and orientation suitability. The third level, technical potential, further converts the physical potential into electrical energy output by applying PV system efficiency parameters, including cell conversion efficiency, temperature-related losses, inverter efficiency, and shading-induced losses. In the literature covered in this review, solar potential most often refers to physical or technical potential evaluated at the individual building level or aggregated to the city scale and above; the methods reviewed in Section 3 operate predominantly at these two levels. A fourth level, economic potential, which incorporates installation costs, electricity prices, and policy incentives, is rarely addressed in the data-driven methods reviewed in this paper.

Solar irradiance on building surfaces has three components: beam radiation arriving directly from the solar disk, diffuse radiation scattered by the atmosphere, and radiation reflected from surrounding surfaces and the ground, quantified by the surface albedo. The reflected component, governed by surface albedo, can be substantial for facades in dense urban canyons, where multiple reflections between buildings increase effective irradiance beyond what direct and diffuse components alone predict.^{16,53–55} For building-scale evaluation, these components must be transposed from the horizontal plane to the plane-of-array (POA) of each inclined or vertical surface using anisotropic sky models, most commonly the Perez model.⁵⁶ Among the parameters governing this transposition, the sky view factor is the most consequential for urban solar analysis. It is determined by the surrounding three-dimensional geometry and serves as the key morphological parameter linking urban form to the solar irradiance received by each building surface.

The conversion from POA irradiance to PV power output follows a well-established physical chain accounting for cell temperature, inverter efficiency, wiring, and shading losses.^{57,58} In data-driven building solar studies, these factors are typically simplified to a single system performance ratio, most commonly ranging from 0.75 to 0.85^{59,60} which is multiplied by the annual POA irradiance and the available PV area to yield the estimated annual electricity generation.

Data sources for building solar potential evaluation

The data-driven methods reviewed in this paper depend on six categories of input data, summarized in Table 1. The choice of data source places an upper bound on the spatial resolution, spatial scale, and temporal resolution

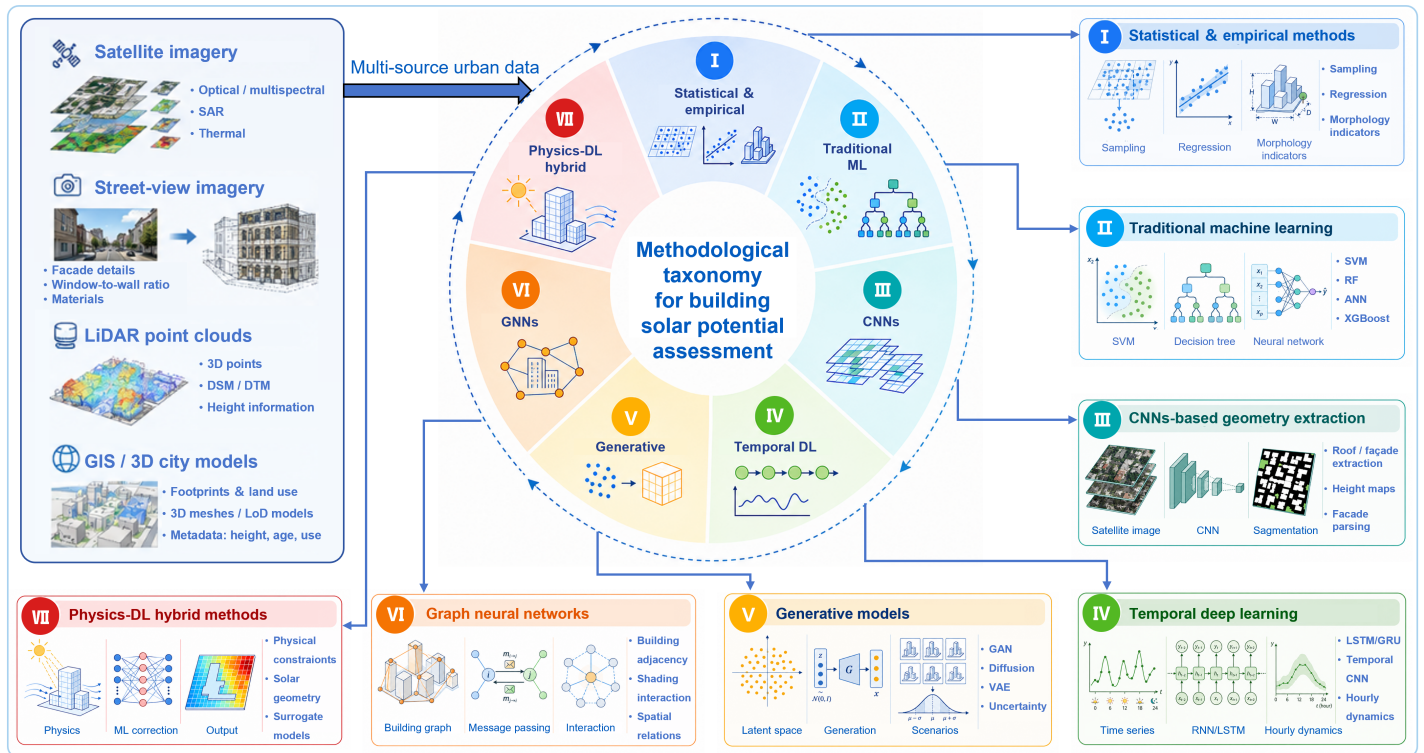


Figure 1. Overview of data-driven methods for building solar potential evaluation.

achievable by any method, although super-resolution and other enhancement techniques can partially mitigate these constraints.

Optical satellite imagery (0.3 to 10 m) is sufficient for identifying individual buildings and estimating rooftop area at the city scale and above; larger rooftop superstructures can be detected at fine resolutions.^{18,30} Aerial imagery offers intermediate resolution (0.05 to 0.5 m) and is commonly used for detailed roof characterization and as training data for automated building extraction. Airborne LiDAR provides dense 3D point clouds from which digital surface and terrain models (DSM/DTM) are derived, enabling roof slope extraction, aspect, and detailed geometry. LiDAR coverage, however, is expensive and concentrated in Europe and North America. Street-level imagery provides centimeter-resolution of building facades and has become increasingly important as research shifts from rooftops toward facades. 3D city models and GIS datasets (LoD1 to LoD3) supply building footprints, heights, and roof geometries at the city scale and are frequently combined with satellite or aerial imagery. Meteorological and solar radiation data from ground stations, satellite-derived products such as CAMS, and reanalysis datasets including ERA5 provide irradiance and temperature at points to 30 km spatial and hourly-to-monthly temporal resolution.

A persistent challenge for building solar potential evaluations via data-driven methods is the geographic imbalance in the availability of the data types listed in Table 1. High-resolution LiDAR coverage and detailed three-dimensional city models are concentrated in a small number of cities, while the majority of the world's urban areas, particularly in the Global South, lack these resources. Satellite imagery and global meteorological reanalysis data are more uniformly available and have therefore enabled a broader geographic scope of study. However, the resulting concentration of research on data-rich locations, with approximately 50% of published studies focusing on Chinese cities and roughly 20% on European cities, limits the generalizability of methods developed to date to the urban regions where solar potential evaluation may be most urgently needed.

DATA-DRIVEN METHODS TO EVALUATE BUILDING SOLAR POTENTIAL

This section traces the methodological progression of data-driven approaches used in building solar potential evaluation, organized by increasing model complexity, spatial and temporal granularity, and physical detail. As presented in Figure 1, seven methodological groups are identified, ranging

from statistical sampling and empirical relationships to physics-DL hybrid methods. The methods are characterized by typical input data, modeling approaches, spatial and temporal granularity, and representative studies.

Statistical and empirical methods

The earliest scalable approaches for building solar potential evaluation employed statistical sampling and empirical relationships to estimate available roof area and solar access from limited data. These methods operate at coarse spatial granularity, typically from the block to the national scale, produce annual-average estimates, and make significant simplifying assumptions about building geometry and inter-building effects.

Statistical sampling methods were used to estimate available roof area by extrapolating from representative samples, distinguishing PV-usable roof area from total building footprint through utilization factors. Such utilization factors varied significantly from 0.22 to 0.98 by building type and land use.^{65,66} Yang et al.⁶⁷ sampled roof orientation distributions from a representative district in Västerås, Sweden. A range of utilization factors was then applied to roof with different orientations, considering shading effects and obstacles. The results were then extrapolated to the entire Swedish building stock, yielding 65 to 84 GWP of rooftop PV capacity across different PV installation scenarios. Gagnon et al.⁴² combined this approach with LiDAR-derived roof characteristics from 128 US cities and built regression models linking census-tract variables to rooftop area, extending to areas without LiDAR coverage. The national scale estimation on rooftop PV capacity was 1118 GW, generating 1432 TWh of electricity per year.

Empirical regression approaches were used to link urban morphology indicators, such as building density, plot ratio, sky view factor, and compactness indices, to solar irradiation.^{53,68,69} Calcabrini et al.⁷⁰ used two simplified indices, i.e., sky view factor and sun coverage factor, to predict local annual accumulated irradiance, preserving accuracy while substantially reducing computation time. Among these studies, a consistent finding is that facade solar potential is substantially more sensitive to urban form than rooftop potential. Increasing building compactness reduced facade PV potential from 20% to 3%, while rooftop declined only from 94% to 79%.¹⁷ On the other hand, morphology optimization could improve facade irradiation by up to 45%, while rooftop irradiation could only be improved by 9%.²⁰

However, statistical and empirical methods share fundamental limitations.

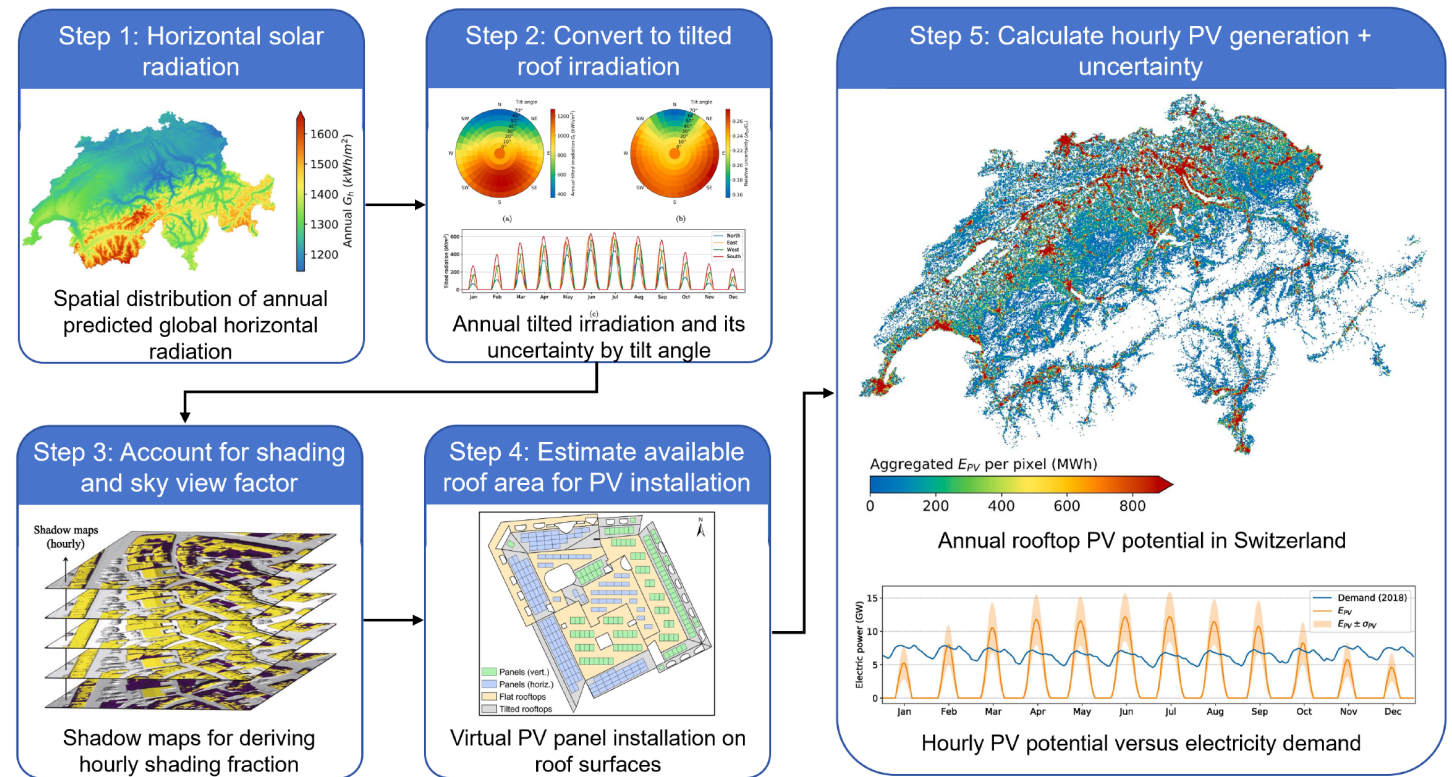


Figure 2. National scale rooftop solar potential evaluation.¹⁰

They assume linear or near-linear relationships between predictors and solar potential, whereas inter-building shading effects are fundamentally nonlinear, and the rooftop availability is difficult to model. They operate at coarse spatial granularity and rely on annual averages that cannot capture the hourly dynamics needed for grid integration and storage sizing. Existing studies have been underlining that nonlinear models such as XGBoost and ANN consistently outperform linear regression for solar potential prediction.^{39,40}

Traditional machine learning

Traditional ML methods, including support vector machines (SVM), random forests (RF), artificial neural networks (ANN), and gradient boosting algorithms, can capture nonlinear input-output relationships without requiring explicit physical equations. These methods typically operate at the rooftop-to-national scale with annual-to-hourly temporal granularity.

Early applications used SVM regression with GIS data for national-scale rooftop PV assessment,⁹ and RF was subsequently adopted for roof shape classification to refine PV estimates by roof type.⁶¹ The shift to tree-based ensemble methods, particularly quantile regression forests, enabled the quantification of uncertainty through prediction intervals. The building solar potential was characterized as a range rather than a single value. Walch et al.¹⁰ demonstrated this at the national scale with hourly resolution, reporting 24 plus or minus 9 TWh per year for Switzerland with full uncertainty propagation (see Figure 2). On the global scale, XGBoost trained on over 300 million building footprints estimated a technical potential of 27 PWh per year.⁷¹

ML models have also been employed as surrogates for physics-based solar simulation. ANNs trained on simulation outputs predicted solar radiation from climatic and geometric variables with high accuracy across diverse urban configurations.^{35,72,73,74} RF surrogates demonstrated comparable accuracy to physics-based simulation with substantially reduced computation time.^{15,36} Zhao et al.⁷⁵ used RF to predict a solar occlusion correction ratio (accounting for shading impacts) from four morphological predictors, estimating the influence of shading on annual accumulated irradiance instantaneously with a relative error less than 0.03%.

The coupling of RF with SHAP (SHapley Additive exPlanations) has marked a transition from purely predictive models to interpretable ones that reveal which urban form parameters most strongly influence solar potential. Key

parameters identified include plot ratio, building floor count, building density, and perimeter shape factor for facade irradiance, with a combined importance of 43.9%.¹⁹ Across 17 tested ML models, XGBoost performed best, and SHAP analysis revealed that roofs accounted for 27% of total building surface area but received 54% of total solar radiation.⁴⁰ Additional specialized applications include RF for diffuse radiation estimation,⁷⁶ clustering-based ML for shadow and solar reflection detection,⁷⁷ building-type-based solar potential prediction,⁷⁸ and RF-based building height estimation from GIS data for constructing 3D building models in rural areas where such models are unavailable.⁷⁹

Convolutional neural networks for geometry extraction

CNNs represent a significant advance in spatial granularity. Whereas statistical and traditional ML methods operate on tabular data, such as building attributes and morphology metrics, CNNs learn directly from spatial data in the form of imagery. This enables analysis at the sub-meter, pixel level of individual roof planes and facade surfaces, and eliminates the requirement for pre-existing building geometry as an input.

Early applications used U-Net architectures for satellite-based rooftop segmentation, eliminating the need for LiDAR or pre-existing 3D building data and enabling city-scale solar mapping from imagery alone.^{37,38} Subsequent studies combined semantic segmentation with optimized spatial sampling, reducing training data requirements while extending coverage to national scales and data-sparse conditions.^{43,62,80,81} Zhang et al.⁸² compared the rooftop segmentation performance of U-Net and DeepLabv3+ with four different backbones, finding that U-Net with a ResNet50 backbone outperformed all alternatives by a clear margin, demonstrating that backbone choice can matter more than architecture choice for rooftop segmentation tasks.

Most rooftop segmentation studies treat roofs as flat, empty surfaces, which systematically overestimates PV potential. Building on the finding that physical shading and reduced rooftop availability must be modeled jointly rather than independently,^{18,83,84} Li et al.⁶³ developed a DL framework that explicitly segments roof superstructures, demonstrating that overestimation varies by building type and urban density. At larger spatial scales, attention-enhanced architectures enabled provincial-scale evaluation across 13 cities with type-specific utilization coefficients.⁸⁵ Evaluation at a similar mega-

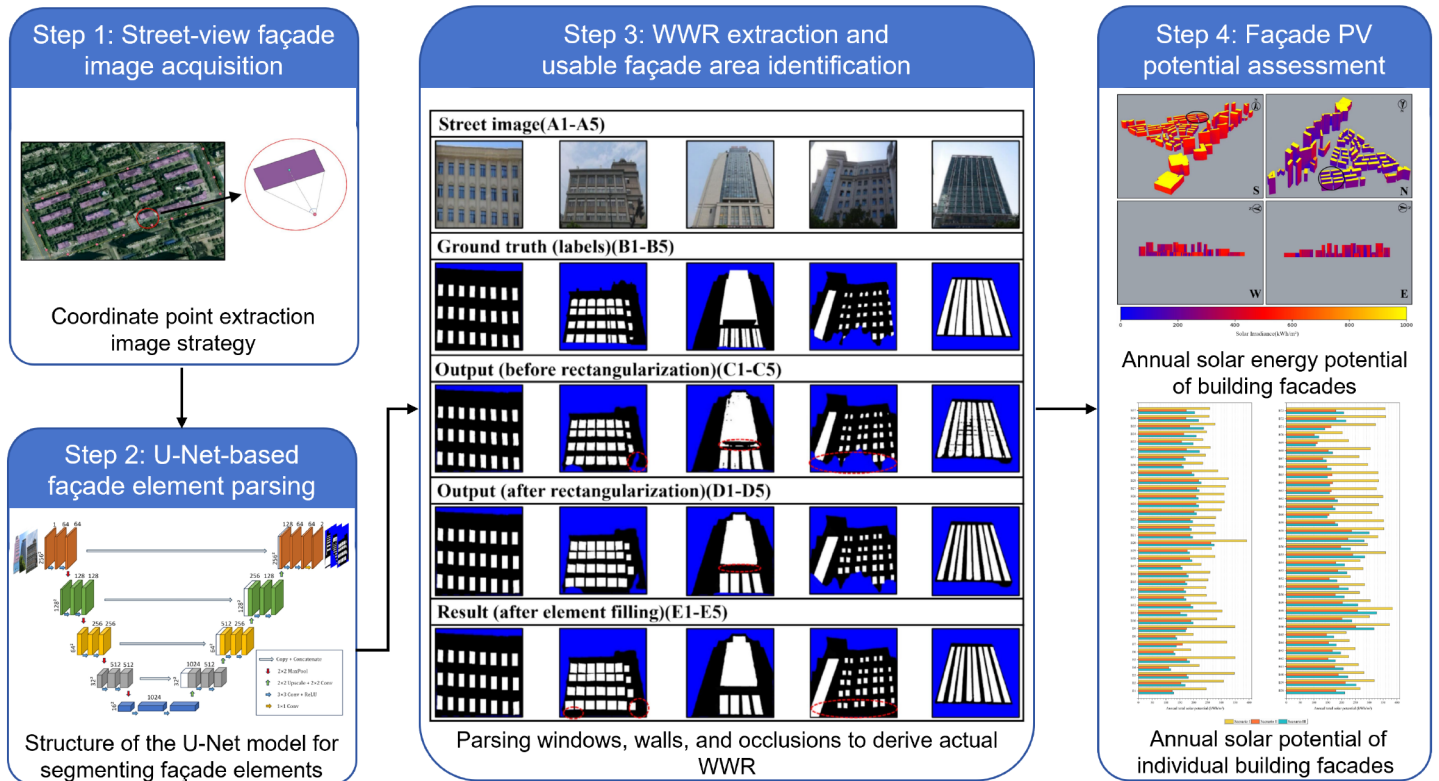


Figure 3. Extracting available facade area from street-view images.⁸⁸

opolitan scale was also achieved by SAM (segment anything model)-based segmentation.⁸⁶

Facade evaluation requires street-level rather than overhead imagery to resolve the windows, walls, and balconies that determine PV-suitable surface area. As presented in Figure 3, DL-based parsing methods extracted window-to-wall ratios and facade elements from street-view and panoramic imagery.^{32,54,87,88} Automated extraction significantly altered building energy model rankings compared with uniform assumptions, demonstrating the importance of measured over estimated facade parameters.³²

Where 3D city models are unavailable, DL-based methods could construct building geometry from two-dimensional data. Mono-to-3D reconstruction from satellite imagery enabled combined rooftop and facade PV evaluation by learning both rooftop outlines and building heights from a single image, bypassing the need for LiDAR or pre-existing height data.⁸⁹ Point cloud and high-definition map approaches offered alternatives to mesh-based 3D representation.^{90,91}

Temporal, graph-based, and generative deep learning

Temporal deep learning models such as recurrent neural networks (RNNs) and their variants predict temporal sequences. RNN-based architectures have been widely applied to predict irradiance from meteorological time series in existing studies, such as the LSTM (long short-term memory) - based model predicting hourly solar irradiance.⁹² This enables a shift from annual-average estimates to hourly and sub-hourly temporal granularity, capturing the diurnal and seasonal dynamics. Such information could be useful for on-site consumption, grid integration, and storage sizing.

GNNs are considered suitable for building solar potential evaluation because buildings in a city could be represented as a graph. Nodes in the graph represent individual buildings and edges encode spatial relationships such as adjacency, mutual shading, and inter-reflection. Unlike CNNs, which operate on regular pixel grids, or MLPs, which treat buildings as independent entities, GNNs explicitly model how each building's solar potential is influenced by neighboring ones.

The GNN line of research on facade solar potential progressed through three increasingly refined architectures. The geospatial graph attention network (GGAT) incorporated building coordinates and inter-building distances into the attention mechanism, learning which neighboring build-

ings most significantly shade each facade surface.⁹³ The multi-layer geo-attention GNN extended this by dividing each facade into ten vertical layers, capturing the vertical gradient of solar irradiance on facades.⁴⁷ The shadow-attention GNN further incorporated height angle and distance between buildings into the attention computation, achieving a coefficient of determination of 0.96 across all building surfaces and saving 97.4% of computation time compared with physics-based simulation.⁹⁴

Spatiotemporal models extend the temporal learning capability and the spatial reasoning of DL techniques by modeling spatial and temporal dependencies. An early application of spatiotemporal graph convolution to urban building energy incorporated solar-based shading as edge weights between buildings, demonstrating that modeling inter-building relationships improved prediction accuracy most during summer and winter daytime hours, when heating and cooling loads are sensitive to solar exposure.⁹⁵ Yang et al.⁹⁶ adapted this paradigm to rooftop PV potential, combining graph convolutional networks for spatial shading characterization with LSTM for hourly irradiance prediction. Their architecture addressed the complementary weaknesses of purely geospatial methods, which struggle with hourly precision at the urban scale, and purely temporal methods, which overestimate potential by neglecting inter-building shading effects.

Generative models learn the underlying patterns and statistical distributions from training data and produce new samples based on the information learned. In the domain of building solar potential evaluation, generative models produce synthetic imagery that substitutes for either scarce training data or computationally expensive physics-based simulation, addressing the issues of limited datasets and prohibitive computational costs.

Diffusion models were previously introduced to the PV domain for dataset augmentation, with synthetic training images achieving higher accuracy than conventional augmentation techniques.⁴⁶ For solar potential evaluation, a generative framework, i.e., CycleGAN, was developed to directly convert facade images into pixelwise segmentation masks, enabling facade segmentation without the need of paired training data.⁹⁷ In contrast, pix2pix, i.e., a conditional GAN that requires paired training data, was applied to facade images, segmenting the facade into available, windows, and unavailable categories and estimating utilization factors.¹⁴

Generative models can also learn the input-output mapping of physical simulation. SolarGAN (as presented in Figure 4) combined a variational

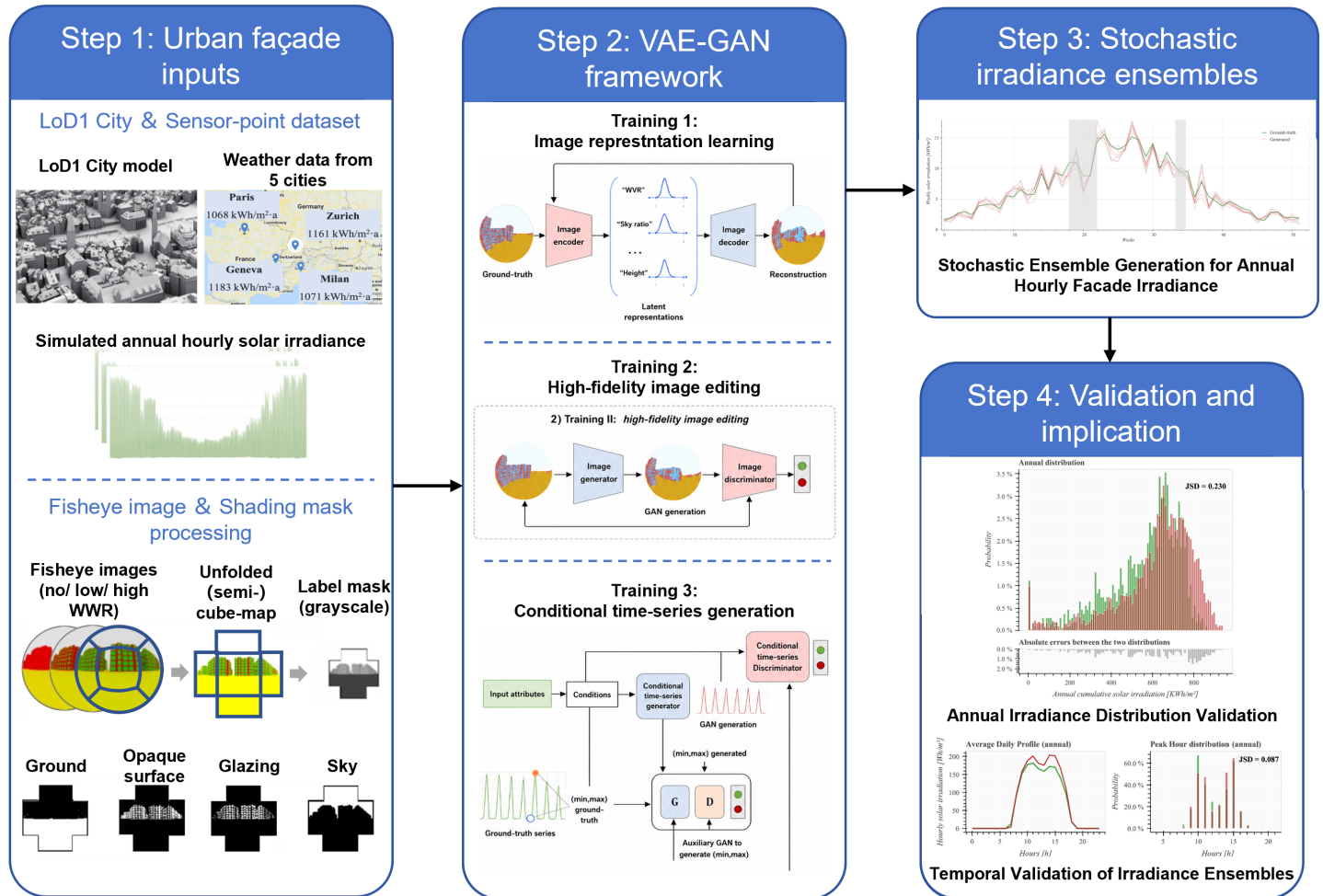


Figure 4. Generative model SolarGAN to predict facade irradiance.⁴⁵

autoencoder with a GAN to map fisheye urban environment images to annual hourly facade irradiance.⁴⁵ It is noteworthy that the SolarGAN generated stochastic ensembles that capture solar intermittency, which is a capability beyond deterministic physical simulation. Deep Umbra used a conditional GAN to map 3D building geometry directly to annual shadow accumulation, replacing explicit ray-tracing and generalizing to urban morphologies unseen during training.³⁸

Physics-DL hybrid methods

A limitation of purely data-driven methods is that they can produce physically implausible results when extrapolating out of the training data. Physics-DL hybrid methods address this, including physical information in the evaluation framework and embedding domain knowledge into DL architectures. These methods aim to combine the accuracy and generalizability of physical models with the speed and flexibility of data-driven approaches.

A distinct line of work integrated 3D building geometry with deep learning-based surface segmentation and coupled GIS-assisted physical shading with DL-identified available surface area. Ren et al.¹⁸ established this paradigm for high-density Hong Kong, using a double U-Net to identify rooftop obstacles which was subtracted from rooftop outlines extracted from 3D-GIS data, to obtain available rooftop area. Meanwhile, dynamic shading effects were evaluated via a physical model based on 3D-GIS data. The results highlighted that shading and rooftop obstacle effects must be modeled jointly rather than independently, as summing their separate reductions overestimated total loss by 26%. Ni et al.⁹⁹ applied a similar framework to Shanghai. Xu et al.⁸⁸ adapted the paradigm from rooftops to facades, integrating GIS-based physical shading with DL-based facade segmentation.

Rather than running physics alongside deep learning, a complementary strategy is to inject domain knowledge into the DL architecture. Li et al.⁶³

encoded the physical relationship between roof geometry and superstructure placement into a multi-task architecture (i.e., SolarNet+), learning rooftop outline, rooftop orientation, and superstructures jointly so the network could understand that these tasks are coupled. Li et al.¹⁰⁰ used land-use classification as a prior. Buildings were pre-categorized into commercial, industrial, and residential types before rooftop segmentation, on the basis that rooftop morphology differs systematically across building types. The pre-categorization improved the F-measure of the segmentation results by 12%.

The above studies kept physics outside the DL model by computing in parallel or encoded into the DL architecture before training. On contract, Dong et al.¹⁰¹ developed SolarCViT, i.e., a hybrid CNN-Transformer trained to internalize shading behavior by learning from physics-based simulation. It fused CNN-extracted geometric features with solar position and irradiance through attention, then refined the combined representation through a Transformer encoder and a progressive decoder to produce the facade irradiance map. The SolarCViT was trained on 237,000 physics-simulated irradiance maps from Shenzhen, achieving a mean absolute error of 8.15 W/m², and was 48 times faster than the model that generated the training data.

The Local Climate Zone (LCZ) framework provides a standardized taxonomy of urban regions and has emerged as an effective bridge between physical modeling and ML. By classifying the urban regions before simulation, LCZ ensures that training data could sample a wider range of building configurations rather than over-representing dominant types. Chen et al.¹⁰² coupled LCZ classification with 3D building models and ML to produce city-scale solar irradiance maps, using the LCZ classes to guide both physical simulation and data-driven model development. Chai et al.¹⁰³ combined LCZ-stratified Ladybug simulations with XGBoost and SHAP analysis, achieving a coefficient of determination of 0.99 for both rooftop and facade PV potential prediction at the city scale. In both studies, LCZ was used as a pre-analytical

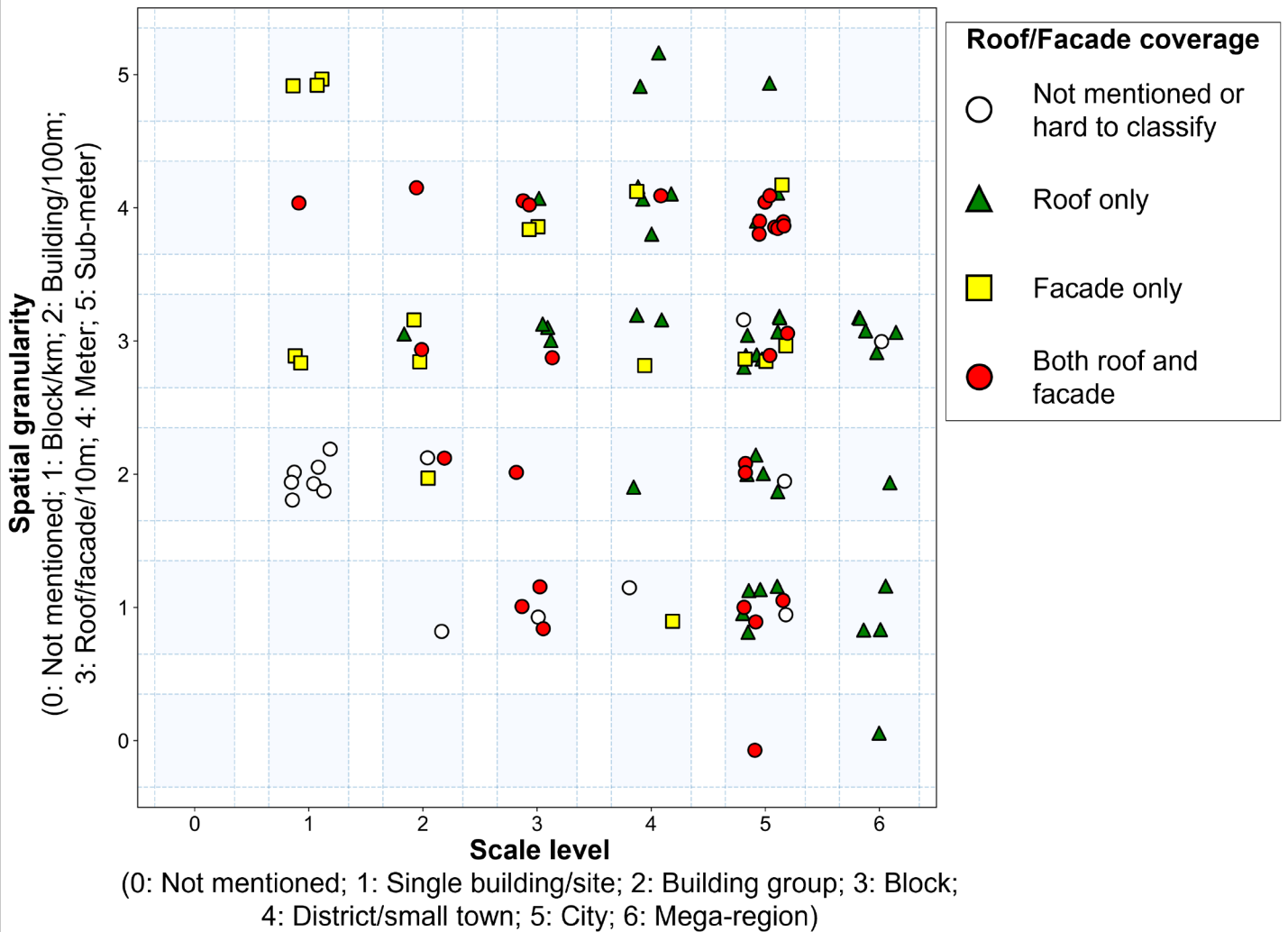


Figure 5. Spatial scale and spatial granularity of individual studies listed in Appendix A (where each point is manually and randomly offset from its actual level for better visualization).

framework, organizing the urban morphology space before simulation or training. This could help the resulting ML model achieve better generalization performance across the full diversity of urban form rather than only the configurations most common in the training set.

Analysis on spatial scale, spatial granularity, and temporal granularity

Existing studies are analyzed on three dimensions, i.e., spatial scale, spatial granularity, and temporal granularity, which range from single building/site to mega-region, block-level to sub-meter, and annual to minute-level. Detailed results are summarized in Appendix A. Figure 5 presents the spatial scale and the spatial granularity of individual studies, in which each point represents one study listed in Appendix A. The spatial scale level of a major part of the studies is at the city level. Several studies conducted mega-region solar potential evaluations. However, the facade potential was underrepresented in mega-region scale studies. Data-driven methods achieving sub-meter-level or meter-level granularity are confined to city-level spatial scale.

Figure 6 presents the spatial scale and the temporal granularity of individual studies, in which each point represents one study listed in Appendix A. Two studies achieved minute-level evaluation, while such high temporal granularity may provide more precision than the task calls for in building solar potential evaluation for planning and design purposes. A substantial part of the studies achieved hourly temporal granularity, owing to the general availability of hourly meteorological data. There is a gap of temporal granularity between the annual level and the hourly level, with relatively few studies at the quarterly, monthly, and daily levels. Considering abundant sources of hourly weather data and minimum barriers to aggregating the data, their scarcity likely reflects convention rather than constraint. Annual totals have

long sufficed for capacity planning, and hourly resolution is driven by grid integration and storage sizing requirements, while the intermediate levels serve neither established purpose.

The results also showed that rooftops have dominated the literature, accounting for approximately 70% of reviewed studies, yet facades represent a substantial and under-exploited resource. It is noted that facade potential evaluation is especially underrepresented in studies at the mega-region level with relatively high spatial granularity. Despite the significant potential of facade PV, averaging 68.2% of rooftop potential across 120 global cities and reaching 239% under some urban environments,^{12,13,104} distinct challenges remain unsolved. Vertical surfaces receive less direct irradiance, are more affected by inter-building shading, and feature windows, balconies, and cladding that reduce usable area.¹⁰⁵ Material optical properties, multiple reflections in urban canyons, and vegetation occlusion remain under-modeled and represent opportunities for methodological development.

EMERGING PARADIGMS AND CROSS-CUTTING ANALYSIS

The methodological progression traced in Section 3 established the capabilities and limitations of the reviewed methods. This section examines three developments that cut across or depart from that progression. Section 4.1 addresses urban morphology, a theme that spans all methodological groups from statistical methods through physics-DL hybrids. Sections 4.2 and 4.3 address qualitatively new paradigms that respond to shared challenges of data scarcity and pipeline fragmentation, respectively.

Urban morphology as a key predictor

Early studies used statistical models to correlate aggregated urban form

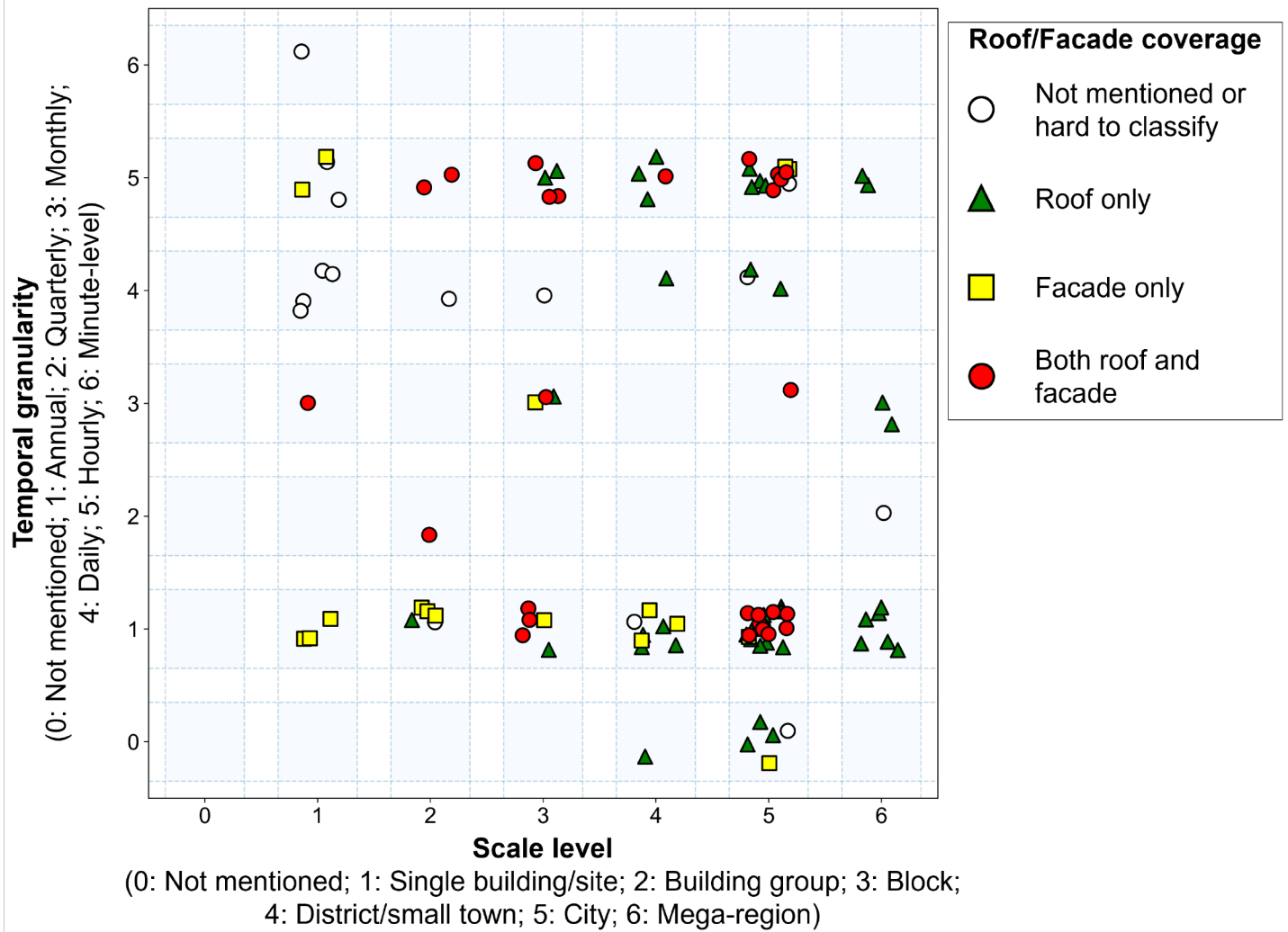


Figure 6. Spatial scale and temporal granularity of individual studies listed in Appendix A (where each point is manually and randomly offset from its actual level for better visualization).

descriptors with solar irradiation. Sarralde et al.²⁰ and Zhu et al.²¹ demonstrated that linear regression on form variables could predict solar potential and guide morphology optimization. Mohajeri et al.¹⁷ and Lee et al.⁶⁸ quantified how compactness and density indicators affect solar access, with Mohajeri et al. revealing that facade solar potential was approximately 5 times more sensitive to compactness than rooftop potential. Calcabrini et al.⁷⁰ demonstrated that just two morphology-derived indicators, sky view factor and sun coverage factor, could predict annual accumulated irradiance with the coefficients of determination above 0.97 for two tested locations (i.e., Delft and Antofagasta) at three different tilted angles (i.e., 0°, 45°, and 90°), bridging physical modeling and morphology-based prediction.

The ML enabled the simultaneous analysis of multiple morphology indicators with nonlinear interactions.^{35,39,104} More recently, interpretable ML methods have revealed which morphology indicators matter most. Tao et al.¹⁹ used RF with SHAP to identify plot ratio, building floor count, building density, and perimeter shape factor as the four dominant parameters for facade irradiance in Hong Kong, with a combined importance of 43.9%. Zhao¹⁰⁶ extended this approach to economic performance, identifying building height, building density, and volume shape factor as the most influential morphology parameters for net present value, levelized cost of electricity, and carbon reduction of facade PV.

Tackling data insufficiency

A practical bottleneck limiting the applicability of the supervised DL methods is their dependence on large quantities of high-quality labeled data, which are unavailable for most of the world's urban areas. Two emerging paradigms, including foundation models and data-efficient learning, provide

solutions to tackle this challenge.

Foundation models leverage pre-training on large and diverse image corpora to reduce the need for task-specific local annotation. Li et al.⁴⁸ developed SolarSAM, an application of a foundation model (Segment Anything Model) in the building solar domain, exploiting zero-shot segmentation to overcome limited local training data for emerging cities lacking detailed street-level data. Dong et al.¹⁰⁷ adopted the Detection Transformer with improved denoising anchor boxes and the zero-shot Segment Anything Model to semantically segment building facades without additional training. Ren et al.¹⁸ and Ni et al.⁹⁹ used pre-trained deep learning models, which were further trained by case-specific datasets, to identify rooftop obstacles in high-density cities of Hong Kong and Shanghai, respectively.

Data-efficient learning approaches modify the training strategy to reduce annotation dependency. Yang et al.¹⁰⁸ used semi-supervised learning for rooftop segmentation, exploiting unlabeled data to supplement scarce labeled examples. Zech et al.¹⁰⁹ demonstrated that Deep Active Learning with entropy-based sampling requires only 3% of labeled data to match full-dataset IoU performance for PV panel segmentation across six datasets in Germany, France, and the US, with results robust across U-Net and SegFormer architectures. Chen et al.¹¹⁰ applied Unsupervised Domain Adaptation for label-free building footprints extraction, combined with DSM data for height estimation, demonstrating a label-free pathway for city-scale solar potential estimation.

End-to-end frameworks

The conventional pipeline for building solar potential evaluation comprises distinct stages, including geometry extraction, irradiance prediction, and PV

performance modeling. End-to-end frameworks collapse these stages into a single model from raw input to PV potential output, eliminating intermediate representations and their associated error propagation.

Dong et al.¹¹¹ developed a scalable end-to-end DL framework (based on End-to-End Anytime Yield Network) that evaluates building facade PV potential from 3D building map instantaneously, which is expected to significantly improve the deployment of facade potential evaluation. Liu et al.¹¹² proposed SF-SPA (Semantic Facade Solar-PV Assessment), an automated framework that transforms street-view photographs directly into quantitative PV deployment evaluations through a pipeline that corrects perspective distortion, performs semantic understanding of facade elements, and applies spatial reasoning for PV layout optimization. Nakhaee et al.¹¹³ developed DeepRadiation, which predicts solar radiation from 360° panoramic streetscape images using Pix2Pix GAN combined with Deeplabv3 and MiDaS, requiring no 3D modeling and delivering results through an augmented reality interface.

CHALLENGES AND FUTURE DIRECTIONS

Despite the rapid methodological progress documented in Sections 3 and 4, several significant gaps persist across the literature, each pointing toward specific directions for future work.

1. Coupled high spatiotemporal granularity at scale. As discussed in Section 3, no study has simultaneously achieved hourly temporal granularity and sub-meter spatial granularity at the city scale or above; the studies closest to this goal each compromise along one dimension. Methods achieving meter resolution are confined to the city scale, while those operating at the national or global (i.e., mega-region) scale remain at block-level spatial granularity. Physics-DL methods, especially ones that internalize solar geometry, offer a potential path to models across scales without sacrificing resolution. However, this remains an open research problem.

2. Validation and standardized benchmarks. Nearly all reviewed studies validate against simulation outputs rather than measured PV production data. A recent physics-based global facade PV evaluation provides a good example. Simulated facade irradiance was compared against Radiance reference results across three climate zones, and modelled PV generation was validated against measured generation from four real PV systems, including one facade installation.¹¹⁴ Beyond individual studies, standardized benchmark datasets across multiple cities and climate zones are absent from the literature. Each study uses different inputs, reference simulations, and metrics, preventing rigorous comparison. The absence of shared benchmarks in turn explains why cross-city generalization remains untested. Only a few studies, such as Deep Umbra⁹⁸, explicitly evaluated performance on urban morphologies unseen during training. It is unknown whether models trained on Shenzhen or Zurich would perform adequately in South Asian or African cities. Foundation models pretrained on global urban imagery, following the early promise of SolarSAM,⁴⁸ could reduce dependency on local training data, but their development requires the multi-city benchmark datasets that do not yet exist.

3. From technical potential to decision-relevant assessment. Nearly all reviewed studies stop at technical potential, i.e., the annual electricity generation from available surface area under local irradiance and standard PV efficiency. Metrics that would support deployment decisions, such as leveled cost of electricity, payback period, grid hosting capacity, and carbon abatement cost, require coupling generation estimates with economic parameters and grid models, which fall outside the scope of almost all reviewed methods. Few studies^{91,106} bridged this gap, while a systematic coupling of data-driven solar potential pipelines with techno-economic and grid integration models would transform the output of the reviewed methods from resource estimates into deployment decision support.

4. Superstructure and obstacle modeling at scale. Rooftop superstructures such as chimneys, HVAC equipment, elevator penthouses, and water tanks reduce available PV area by 26% to 43%, depending on building type and urban density,^{18,30} yet few studies attempt to detect and remove them from satellite imagery.^{18,63,99,100} Facade obstacles present an even greater challenge, with windows, balconies, and heterogeneous cladding requiring street-level imagery and specialized segmentation models.^{14,32} Methods that do address superstructures have been demonstrated only in single cities and

are untested on the architectural diversity of other regions. Closing this gap requires superstructure-aware segmentation models that generalize across regions, and benchmark datasets with pixel-level obstacle annotations, which currently exist for no city at scale.

5. Geographic imbalance. Approximately 50% of published studies focus on Chinese cities and roughly 20% on European cities. The regions with the highest solar resource availability, including the Middle East, North Africa, South Asia, and sub-Saharan Africa, are among the least studied. This concentration is driven by the geographic distribution of the input data types documented in Section 2.2. High-resolution LiDAR and 3D city models are concentrated in data-rich countries, while satellite imagery and reanalysis data are globally available but under-exploited for the Global South. Addressing this imbalance requires open data collection in underrepresented regions, research collaborations with local institutions, and methods specifically designed for data-sparse, rapidly urbanizing contexts. The data-efficient learning and foundation model approaches could provide a starting point.

Conclusion

The convergence of remote sensing, computer vision, and data-driven methods has transformed building solar potential evaluation from a manual, building-by-building exercise into an automated, city-scale capability. This review has traced the methodological progression from statistical sampling through traditional ML and CNNs to generative models, graph neural networks, and physics-DL hybrid approaches, characterizing the advances along three axes: from simpler to more expressive models, from coarser to finer spatial granularity, and from more simplified to more physically detailed analysis. Alongside this progression, existing studies have seen the emergence of foundation models that leverage pretraining on large-scale visual data, end-to-end frameworks that collapse the multi-stage pipeline into a single learned transformation, and a growing recognition of urban morphology as predictors of solar potential.

The state of the art delivers rooftop extraction accuracy exceeding 96% from satellite imagery, R^2 values above 0.97 for ML-based irradiance prediction at speedups of 16 to 48 times over physics-based simulation, and global-scale building-integrated photovoltaic potential estimation covering 120 cities. Facades, long neglected, are now recognized as a substantial resource. Methods developed specifically for facades, including GNNs that capture vertical irradiance gradients across individual surfaces and generative models that synthesize stochastic irradiance time series, have begun to address the distinct challenges of vertical surfaces. Nevertheless, the field remains concentrated on annual rooftop evaluation, and the transition from simulation-validated prediction to real-world measured PV production has barely begun.

Five challenges define the path forward. The first is achieving coupled high spatiotemporal resolution at the city scale and beyond, which no reviewed study has demonstrated. The second is closing the validation gap. Without measured PV production data, particularly for facades where such data are scarce, the accuracy claims of data-driven methods still rely on simulations. The third is moving beyond technical potential to metrics that support deployment decisions. The fourth is detecting and modeling rooftop superstructures and facade obstacles at scale, a problem that affects PV area estimates by 26% to 43%, yet is addressed by only a few studies. The fifth is correcting the geographic imbalance. Tackling these challenges demands interdisciplinary collaboration across computer science, building physics, urban planning, and energy policy, and a shift of attention toward the regions and building surfaces where the greatest untapped solar potential lies.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

No new data were created or analyzed in this study.