Applied Energy 291 (2021) 116817

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Review of geographic information systems-based rooftop solar photovoltaic potential estimation approaches at urban scales

Abdo Abdullah Ahmed Gassar, Seung Hyun Cha *

Department of Interior Architecture Design, Hanyang University, Seoul 04763, Republic of Korea

HIGHLIGHTS

- GISs-based rooftop solar photovoltaic potential estimation approaches are reviewed.
- Approaches are classified as sampling, geostatistics, modeling, and machine learning.
- All applications and limitations of each approach are reviewed and discussed.
- Machine learning is a promising approach for large-scale rooftop solar PV estimates.

ARTICLE INFO

Keywords:
Building rooftops
Geographic information systems
Solar photovoltaic potential
Estimation approach

ABSTRACT

In urban environments, decentralized energy systems from renewable photovoltaic resources, clean and available, are gradually replacing conventional energy systems as an attractive source for electricity generation. Especially with the availability of unexploited rooftop areas and the ease of installation, along with technological development and permanent cost reductions of photovoltaic panels. However, the optimal use of these systems requires accurate estimates of supply (rooftop solar photovoltaic potential) and the design of an intelligent distributed-system integrated with power grids. Geographic information systems (GISs)-based estimation is justified as a promising approach for estimating rooftop solar photovoltaic potential, in particular, the possibility of combining GISs with LiDAR (Lighting-Detection-And-Ranging) to build robust approaches leading to accurate estimates of the rooftop solar photovoltaic potential. Accordingly, this study aims to present a comprehensive review of GISs-based rooftop solar photovoltaic potential estimation approaches that have been applied at different scales, including countries. The study classified GISs-based approaches into sampling, geostatistics, modeling, and machine learning. The applications, advantages, and disadvantages of each approach were reviewed and discussed. The results revealed that GISs-based rooftop solar photovoltaic potential estimation approaches, can be applied to the large-scale spatial-temporal assessment of future energy systems with decentralized electrical energy grids. Assessment results can be employed to propose effective-policies for rooftop photovoltaic integration in built environments. However, the development of a new methodology that integrates GISs with machine learning to provide an accurate and less computationally demanding alternative to LiDAR-based approaches, will contribute significantly to large-scale estimates of the solar photovoltaic potential of building rooftops.

1. Introduction

Accelerated global urbanization along with population growth and climate change, represents a significant challenge in terms of formulating energy policies and creating sustainable built urban environments. In particular, renewable energy sources still account for only 19.2% of the current energy consumption [1]. Moreover, approximately 55% of the global population is concentrated in cities; and this percentage is expected to reach 68% by 2050 [2] and to continue growing, with a population of 10.9 billion by 2100 [3]. This is in addition to the approximately 230 billion m^2 of new urban infrastructures expected by 2060 [4]. This means that the urban areas, and specifically cities, will face enormous challenges regarding energy demands, which will, in turn, coincide with an increase in greenhouse gas emissions from buildings, including carbon emissions. Especially since cities are

* Corresponding author.
E-mail addresses: gassar@hanyang.ac.kr (A.A.A. Gassar), chash@hanyang.ac.kr (S.H. Cha).

https://doi.org/10.1016/j.apenergy.2021.116817
Received 28 October 2020; Received in revised form 30 December 2020; Accepted 28 January 2021
Available online 1 April 2021
0306-2619/

Nomenclature

Functions

G_h	horizontal solar radiation at earth's surface
G_B	direct beam component
G_D	diffuse component
G_t	tilted radiation
G_{Bt}	direct tilted radiation component
G_{Dt}	diffuse tilted radiation component
G_{Rt}	reflected tilted radiation component
SVF	sky view factor
S_{sh}	shaded area coefficient
A_{pv}	suitable rooftop area
A_t	tilted rooftop area
C_{sh}	shaded area coefficient
C_{pv}	hourly shading fraction of rooftop
S_{sh}	the remaining roof area
E_{pv}	rooftop area output
μ_{pv}	PV panel efficiency
PF	performance factor

Abbreviations

ANNs	artificial neural network
SVM	support vector machine
RF	random forest
GB	gradient boosting
MLR	multiple linear regression
KNN	k-nearest clustering
KM	k-means clustering
ELME	extreme learning machine ensemble
RC	regression clustering
GIS	geographic information system
SPV	solar photovoltaic
RMSE	root mean square error
SVR	support vector regression
LiDAR	light detection and ranging
PV	photovoltaics
GA	genetic algorithm
BIN	Broadcast interpolation
INDW	Inverse distance weighting
RBFM	radial basis function

responsible for 70% of the overall global energy consumption, accounting for more than two-thirds of carbon emissions [5,6]. Accordingly, effective policies should be implemented in urban environments in view of the increasing energy demands and with an aim to reduce building emissions and other energy pollutants.

Renewable energy sources, including solar photovoltaic (PV) sources, are a promising solution for satisfying the growing demands for building energy [6] and for mitigating energy-related emissions in built urban environments (including cities). In particular, PV energy systems are attractive sources of renewable energy and can easily be integrated with the existing building structures, such as rooftops and facades [7]. According to the expectations of the International Energy Agency (IEA), the share of PVs will grow to 50% of the total renewable energy sources by 2024 [8]. This type of technology, that is, PV panel technology, has been made to offset the electrical energy generation peak from fossil fuels and reduce related carbon emissions [9,10]. PV panel technology is distinguished not only by its ability to generate energy efficiently but also by its potential for becoming an actual component in construction, e.g., acting as an exterior part of building components, such as the façades and rooftops [11–13]; thereby, this technology reduces the material costs of buildings. Moreover, permanent reductions in the costs of PV panels have increased their usage i.e., their wide-spread. Compared with traditional nonintegrated construction systems, integrated PV panel technology can be provided noise protection, weatherproofing, thermal insulation, aesthetic value, etc. [9–11], along with the electrical energy supply. Based on the type and thickness of the constituent material, this technology can be categorized as crystalline, thin-film, concentrating (e.g., gallium arsenide), hybrid (e.g., combination crystalline with non-crystalline), and dye-sensitized technology [11,14,15]. Each type of PV technology has its own advantages and disadvantages, in terms of performance, efficiency, cost, and lifespan. However, PV technology has been improved to be more efficient and applicable when installed in building structures, i.e., this technology can convert buildings from an energy consumers to energy producers [16].

Cities can play a fundamental role in the widespread adoption of PV technology through various forms of local distributed generation [17,18], as city districts represent an ideal scale for incorporating local renewable energy sources with city infrastructures to balance the localized energy demand [19]. In particular, with the availability of existing building structures (i.e., rooftops and facades), there is no need for additional land, as well as reduced use of materials, lower network transmission losses, and fewer network congestion issues [20]. Based on that, PV panel installation on rooftops instead of on facades is ideal. The main reason for this is the angle of inclination (rooftop inclination) at which the PV panels receive sunlight, as well as the rooftop orientation, effects of both trees and shading factors, and aesthetic value. This, in turn, offers a great opportunity to improve building energy efficiency by exploiting rooftops of buildings to mitigate carbon emissions. In particular, the Paris agreement has recognized the global role of cities and urban authorities in addressing climate change and in achieving global reductions in carbon emissions [21]. In this context, the integration of PV panel technology has been recommended (or made mandatory) in new EU buildings, with an aim to address the related aspects of functionality and aesthetics [22].

However, identifying the potential and calculating the efficiency and performance of PV panels on existing building rooftops in city districts are important for designing future urban environments and modifying existing structures [23,24], as well as for integration PV technology with local existing grids. The conversion efficiency of solar photovoltaic energy is defined as the minimum usable electrical energy that can be achieved by a PV cell integrated with building rooftops (i.e., the solar energy converted into usable electricity) when in balance with the indoor environment requirements of buildings. Therefore, a PV cell's efficiency is assessed using a modeling approach based on the energy conservation principle, that is, the analysis and consideration of losses related to the installation of the solar PV energy systems on building rooftops. Thus, there is a need to assess the efficiency of PV technology on building rooftops at the large scales, including in city districts and mega-cities. Therefore, accurate modeling techniques, i.e., estimation approaches, are a fundamental step in achieving this goal [25,26].

Five basic principles should be considered when assessing the feasibility of applying PV panels (solar photovoltaic panels) to building structures i.e., rooftops. First, the total area available on the building rooftops should be estimated. The second principle is that the total area appropriate for rooftops PV panel installation should be calculated. The third principle is that the solar radiation available on building rooftops should be estimated. The fourth and fifth principles are related to the technical and economic aspects, that is, the total usable electrical energy production of integrated rooftop solar PVs and the corresponding investment costs, respectively. However, the optimal solution for adhering to these principles can only be found if they are managed within a comprehensive framework. In other words, it should be searched on an optimal approach that will overcome most of the barriers to evaluating the efficiency of PV panels. Geographic information systems (GIS) techniques represent the optimal solution in this regard. In particular, they have become an essential assessment technique for assessing the application potential of renewable energy sources and demonstrating their local effects [27,28]. GIS-based estimation approaches can evaluate the energy generation potential of renewable sources by considering technical, economic, and environmental criteria [29] and can contribute to developing environmentally friendly power grid settings in different urban areas, including large cities, and countries. Hence, GIS-based developed models have been utilized for national and regional planning [19], and integration of both environmental and energy models in city district planning is recommended for the development of future solar cities [21,30]. In this regard, integrated GIS technology can play a major role in promoting the deployment of rooftop PV panels and implementing so called energy flexibilisation options such as demand-side management and storage [31].

In the traditional estimation approach, the calculation of PV energy production is based on average annual measurements of the available and usable solar radiation in a specific area. The annual solar radiation on surfaces is measured by kWh/m^2/year, and the annual electrical energy generation from rooftop-based PV panels is estimated in kWh; the rooftop area of each building is multiplied by the amount of solar radiation and average discount rate to consider the efficiency rates of PV installations. In recent approaches, in addition to the aforementioned techniques, satellite imagery and digital elevation models created using light detection and ranging (LiDAR) data and GIS techniques have been used. This allows for consideration of the shading effects of the local topography, e.g., around buildings and trees, on solar radiation calculations. The most advanced versions of such models provide information including suitable solar thermal systems, system installation costs, system payback times, potential reductions in carbon emissions, and even the local availability of installers [32]. Moreover, rooftops of buildings that are suitable for PV panels are explicitly shown in online Web-GIS platforms. Thus, building owners can quickly and easily acquire information on the possibilities for using solar energy in their buildings. Additionally, the information can help public administrations in developing sustainable regional energy supply programs and setting PV-penetration targets.

Based on the aforementioned analysis, this study seeks to shed light on GIS-based estimation for determining rooftop solar PV potential at various urban scales, by providing a comprehensive review of the research efforts related to PV technology application in previous studies on building rooftops, and creating a simple classification for GIS-based estimation approaches based on their different functions. Furthermore, this study highlights some important aspects regarding PV technology deployment, which should be considered in future urban areas for reducing greenhouse gas emissions (i.e., the promotion of low carbon energy systems) and shifting toward a clean urban environment. This study was conducted to offer a simple and effective method for all readers interested in this field (including researchers) to easily understand how GIS-based estimation techniques contribute to determining the potential for PV technology, and to demonstrate their efficiency in meeting energy demands and reducing building energy-related emissions in different city districts. Moreover, this study aims to show how the integrated GIS contribute to the deployment of PV technology at the city and municipal scale and how GIS-based approaches dealt with challenges related to the lack of input data at large urban scales. More specifically, the main motivation behind this study is to address the lack of reviews in the field of GIS-based solar PV potential estimation approaches applied to building rooftops. Previously published reviews [7,33,34,35,36] on PV energy systems in buildings covered other aspects of PV applications (such as technical aspects) instead of rooftop PV potential estimation approaches; in contrast, this study only considered the GIS-based PV estimation approaches applied to building rooftops, to provide a more specific review.

The key objective of this study is to present a comprehensive review of GISs-based estimation approaches applied to rooftops, which are used to investigate the potential of solar PV energy system deployment in built urban environments. This is accomplished by classifying the approaches and then providing a comprehensive review of the applications of those approaches at different urban scales, including cities and countries. In this context, the contributions of this review are: 1) to provide a detailed background of GISs-based estimation approaches for rooftop solar PV potential estimates; 2) to review different applications of such GIS-based estimation approaches; 3) to discuss the advantages and disadvantages of each GIS-based estimation approach in the context of urban buildings to determine the most effective estimation approach for investigating the potential of rooftop PV energy estimates at different urban scales; and 4) to identify a number of key future research tasks that should be considered for enhancing rooftop solar PV potential estimates to better contribute to the deployment of low carbon energy systems. This remainder of this paper is organized as follows. Section 2 describes PV technology and GIS techniques. Section 3 describes the study methodology. Section 4 classifies GISs-based estimation approaches and presents and analyzes their applications at different urban scales. Section 5 discusses the challenges and obstacles encountered when applying GIS-based estimation approaches to rooftops at different urban scales. Section 6 summarizes the main findings and draws future research direction.

2. Related background

2.1. Solar photovoltaic (PV) technology

PV technologies comprise "photovoltaics"/"solar panels" that convert sunlight (i.e., solar radiation) directly into useful electrical energy, which is utilized in the heating, cooling, and lighting of buildings. The working principle of this technology is usually based on the presence of a light-absorbing material within the device structure, e.g., a semiconductor material, which absorbs the photons in light and generates free electrons based on the PV effect. Based on this effect, the PV cell gains energy from sunlight when sunlight is incident on it, and releases electrons. A built-in potential barrier in the PV cell acts on those electrons to produce a voltage that is utilized to drive a current through a circuit [8,37]. PVs can be either opaque or semi-transparent. The semi-transparent type can be incorporated in the roofs, walls, and windows of buildings, whereas the opaque type cannot be incorporated in the windows of buildings, i.e., only with walls and roofs [23,38,39]. According to the materials used in their fabrication, PV panels can be classified as silicon, cadmium, organic and polymer, hybrid and thin film panels [8,37], as summarized in Table 1.

The incorporation of PV panels into building structures (including rooftops) began in the late 1990 s, as an attractive and useful technology for offsetting the peak demands of electrical energy in buildings [40] and reducing related greenhouse gas emissions. The incorporation of PV panels utilizes unused building structures, and the panels are installed either horizontally on rooftops [41–46] or vertically on the sides of structures, such as facades i.e., walls and windows [47–52]. Therefore, the installation placement should consider related-influential factors, including the amount of available solar radiation at the building surfaces, building elevations, operating and installation costs, urban densities, system component lifespan, and urban morphology. In this context, precise data on both received solar radiation and available suitable rooftop areas in target buildings is the most important element for the successful planning and operation of PV energy systems in built urban environments. Byrne et al. [34] studied the possibility of deploying PV energy systems in Seoul buildings by considering the received solar radiation and available appropriate rooftop areas. They found that nearly 30% of the city's total annual electrical energy demand could be provided by rooftop-based distributed PV panels. Likewise, Schallenberg-Rodriguez [33] found that utilizing 45% of the total rooftop areas of buildings in the Canary Islands could provide approximately 9000 GWh of the total electrical energy needs for buildings.

Table 1
Classification of solar photovoltaic technologies integrated with building structures based on their basic physical configurations [8,37,45].

Category		Advantage	Disadvantage
Silicon	• Monocrystalline silicon PV panel • Polycrystalline silicon PV panel • Amorphous silicon PV panel	• High efficiency • Stable performance • Aesthetics • Easy to test, more accurate under sunlight	• Prime cost • A high amount of semiconductor material required per cell
Cadmium	• Cadmium telluride PV panel • Cadmium sulphide PV panel	• Stable performance • Low cost	• Low efficiency • Low aesthetic value
Hybrid	• Hybrid PV panel	• Good performance, • Good efficiency	• High prime cost • Short lifetime • Limited for appliances • Dependence on hybrid inverter capacity
Organic and polymer	• Organic PV panel	• Low cost	• Performance and efficiency are so limited • Stable in dark, degrade in light conditions
Thin film	• Thin film PV panel	• High efficiency • Aesthetics • Light-weight • Small amount of semiconductor material required per cell	• Prime cost • Less stable • Short lifetime

Moreover, Bergamasco and Asinari [53] presented a methodology integrating a GIS and solar radiation map to estimate the energy generation potential of PV panels on the rooftops of Piedmont buildings in northwestern Italy. The investigations involved scenarios, and the results revealed that building rooftops integrated with PV panels could significantly contribute to providing electrical energy in buildings, especially as the solar energy potential reached 6.9 TWh in the year examined (according to the best scenario). Izquierdo et al. [54] conducted a quantitative study to identify available areas of rooftops for PV energy applications in Spain. The assessment results showed that installation of a solar-hot-water system and PV panel system could satisfy 68.5% and 4% of the energy demands in buildings for hot-water and electricity, respectively. In addition, Jacques et al. [55] presented an evaluation methodology that combined a roof segmentation algorithm with low-resolution-LiDAR-data to calculate the PV capacity for small and large rooftops of buildings in Leeds, UK. They conducted that this methodology could be an effective planning tool for informing individual building residents on the PV capacity of their buildings. Kabir et al. [56] studied the feasibility of applying PV panels on building rooftops in Dhaka, Bangladesh. They observed that the buildings had approximately 134.282 km^2 of bright rooftops, and that PV panel application (75 W) could provide 1000 MW for the electrical energy needs of city buildings.

Several investigation studies have been conducted to identify the electrical energy generation potential of rooftop-based PV systems across various levels, ranging from individual buildings to national and regional levels, with the aim of widening the applicability of rooftop-based PV technology and reducing energy-related emissions in buildings. In Hong Kong, Peng et al. [57] conducted an in-depth-investigated of rooftop PV panel deployments and their environmental advantages. They estimated PV electrical energy production on rooftops to be 5.97 GW, which could satisfy 14.2% of total annual electrical energy demands in Hong Kong. Additionally, the energy use-related emissions of buildings could be reduced by nearly 3,732,000,000 kg/year. This is consistent with the findings of Yang et al. [58], who reported that an equivalent of 41% of the lighting energy needs could be satisfied by PV rooftop systems installed over a floor area equivalent to 250 m^2. In EU countries, Defaix et al. [59] conducted an investigation on PV system installation on building structures, such as rooftops and facades. The results showed the availability of approximately 951 GWp of PV energy, which could provide approximately 840 TWh of electrical energy to EU buildings. This is equivalent to more than 22% of the predicted annual electrical energy demand in the EU for 2030. Martinopoulos [60] emphasized that the investment costs of rooftop PV systems in EU buildings can be recovered within 5–11 years without any subsidy. In the US, Barkaszi and Dunlop [61] defined two main categories of rooftop-based PV array systems in buildings: building-integrated PV systems and building-attached PV systems. Anctil et al. [62] discovered that the use of PV technologies in US buildings has both cost and environmental benefits, as it combines electricity production and energy consumption reduction. Sadineni et al. [63] studied the effects of the direction of the integrated PV panels with rooftops on the peak demand for household electrical energy and found that the southern direction and 220° are economically optimal; the total annual energy cost compared with that for a reference house of the same size decreased by 38%. Schoen [64] recommended further investments by the Dutch government in buildings integrated with PV technology, to achieve 500 MW of energy generation within the next 7–10 years. Quesada et al. [52], Biyik et al. [65], and Baljit et al. [66] noted that the integration of PV panels with building structures can meet a significant amount of the building electrical energy needs, in addition to reducing cooling and heating loads. Therefore, the solar PV technologies should be prioritized for application to suitable areas in building structures, such as rooftops and facades, to support the gradual transition towards low carbon energy systems in the context of large-scale buildings.

2.2. Geographic information systems (GISs)

GIS techniques are a conceptual framework designed to capture, store, manipulate, analyze, manage, and present all types of spatial or non-spatial data [67–69]. GIS applications are computer-based tools/methods that allow users to create interactive queries, store, edit, and analyze spatial and non-spatial input data, and share the results of the aforementioned operations by presenting them as attribute tables and digital maps [70,71]. The query approach facilitates identification of solutions to several issues encountered in urban planning and design [72], including in the design of building energy systems. Accordingly, the GIS framework is an effective technique/tool for planning and developing urban infrastructures, as well as for modeling and strengthening energy grids at large urban scales. Moreover, it enables planners and designers to digitize objectives, analyze digital urban development models at different levels, and create elevation charts of buildings in 2D and 3D/4D environments [73–76]. In addition, GISs-based models can retain spatial information and other features/attributes.

Consequently, the GIS framework has been applied to support renewable energy modeling (including that for PV panels), and to capture, manage, analyze, and envisage large temporal-spatial and non-spatial datasets. Usually, GIS maps, such as raster and shapefiles maps, are representations of spatial data with attribute tables containing non-geographic data, including information related to built-up areas, building ID, building areas, building types, numbers of floors, and floor areas. These data can be shared as a feature from a geographical map containing geographic-space and attribute data in the ArcGIS information system (a typical ArcGIS software program). A feature can be defined as a small unit for a building or a large unit for a country, depending on the research objective [76]. In other words, the advanced spatial analysis capability of GIS software and its extensions makes its integration with the advanced simulation tools and data-driven analytical techniques useful for modeling and evaluating the potential of renewable energy sources; such energy sources include PV technologies in the context of large-scale buildings [77,78], which can contribute to the development of a "solar city". All of these factors make the GIS framework an ideal candidate for facilitating the utilization tools and other techniques to manage a wide range of data and for complex urban environment modeling.

However, the integration of GISs with urban environment modeling remained unexplored until the 1980s, as part of the GIS community's efforts to develop the analytical abilities of GISs [79]. Today, GISs are integrated with other analytical methods and offer clear advantages in many domains, including the planning and development of urban power grids in city districts and megacities. The ArcGIS CityEngine [80] (CityEngine is an advanced 3D modeling tool for creating and managing built environments in less time than possible using traditional modeling techniques), Quantum GIS (QGIS) [81,82] (Quantum GIS is a free, open-source platform comprising scalable Desktop GIS software with plugin developments in Python and C++) and other tools and techniques, are typical examples of GISs that have been developed to facilitate planning of built environments. In this regard, the ArcGIS platform (a typical GIS software program) can be integrated with data-driven approaches [83–87], such as multivariate clustering, image segmentation, random forests (RFs), multiple regression, support vector machines (SVMs), and artificial neural networks (ANNs), as well as with simulation tools [88–93]. ArcGIS technique allows researchers to conduct several types of analyses using geostatistics or machine learning approaches, including the classification of remote-sensing imagery i.e., satellite images. Deep learning algorithms [94–97] have become a major component of spatial analysis in ArcGIS and can be used to address and manage energy-related problems at large scales, such as in mega-cities. These algorithms can support a wide range of data, including LiDAR, tabular data, feature layers, and even unstructured text. Mastrucci et al. [83] adopted a GIS-based regression statistical approach to estimate the residential gas and electrical energy consumption of buildings in Rotterdam, the Netherlands. They adopted multiple linear regression models because such models allow for the downscaling of the measured energy consumption from the aggregation level to individual buildings, depending on the type of building, number of building occupants, floor area, and building age. Assouline et al. [98] combined a support vector regression (SVR) approach and GIS to estimate the PV electrical energy generation of building rooftops in Switzerland. This was followed by another study by Assouline et al. [84], focusing on integration of a GIS with a RF approach to estimate the rooftop-based PV energy potential across Switzerland. The estimation results showed a significant potential for rooftops PV energy generation in Switzerland.

Data-driven based approaches integrated with GISs are also being utilized as an effective approach for energy planning at different urban scales. Cecconi et al. [99] combined an ANN and a GIS to assess the energy saving potential of school buildings in Lombardy, Italy, based on an open data source. They concluded that GIS is an important tool for formulating energy policies for buildings in Lombardy. Mohajeri et al. [100] combined an SVM approach and a GIS to model and classify the rooftops of 10,085 Geneva buildings, depending on their received solar energy. They used solar radiation analytical tools in the GIS, along with Matlab, to model the solar potentials on the rooftops of buildings at different scales (i.e., at the individual building level, the city district level, and the city level), as shown in Fig. 1. They observed that classification of the solar rooftop shape provides fundamental information for designing new buildings and retrofitting (e.g., for efficient integration with rooftop-based solar energy systems). Likewise, Gagnon et al. [101] integrated a GIS with a regression statistical approach and a LiDAR dataset to determine the potential for rooftop-based PV electrical energy generation across the United States. They found nearly 8.13 million m^2 of suitable rooftops in buildings, with the potential to accommodate 1118 GW of PV capacity, which can generate 1432 TWh of electrical energy per year. Mrowczynska et al. [102] concluded that the combination of GIS techniques with artificial intelligence contributes to supporting an informed decision-making process for renewable energy source investments, as well as local policies related to reductions in individual household energy demand.

In addition, GIS tools have made significant contributions to urban energy modeling, as they can be coupled with energy simulation tools at different urban scales. For example, Nageler et al. [89] combined a GIS tool (QGIS) with the "IDA ICE" software to simulate the urban energy of Gleisdorf buildings. They concluded that a GIS tool has a significant potential for collecting, processing, and analyzing input datasets, and then representing building energy simulation results in the form of a digital map or 3D visualization. Chen et al. [91] used QGIS to split a land use dataset and related attributes to create a parcel geometry with land use-related attributes in the form of a shapefile (.shp). Mastrucci et al. [92] focused on integrating a GIS with a dynamic thermal simulation to

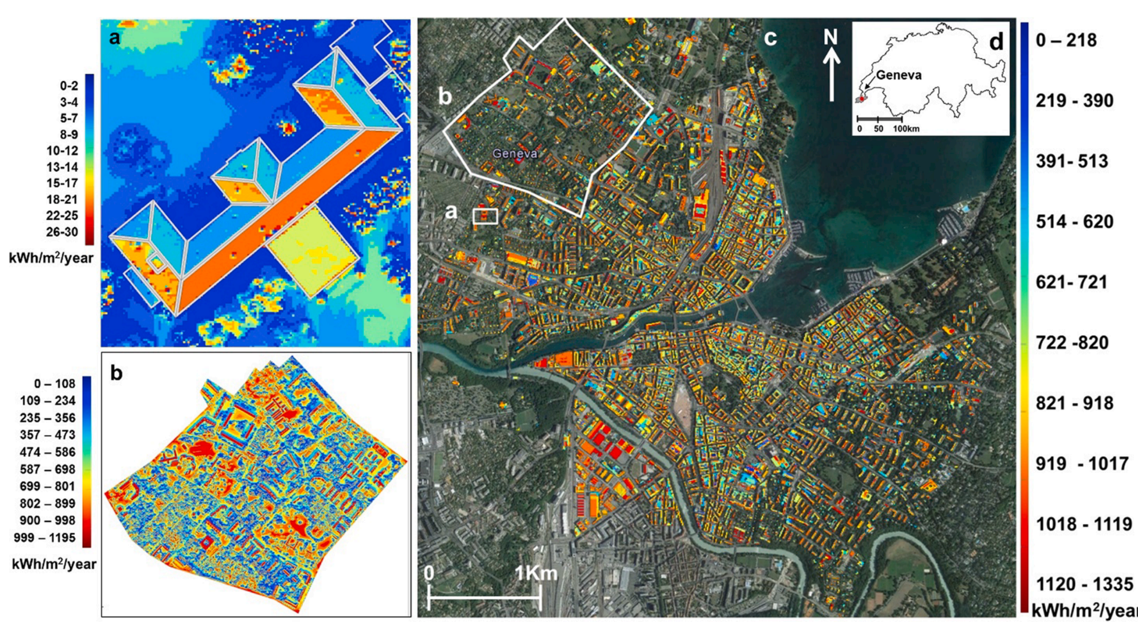

Fig. 1. Annual average estimated solar PV energy in Geneva rooftops at a) the level of a single building rooftop; b) level of city district buildings; c) level of city buildings [100].

estimate the combined impact of retrofitting measures on the heating demands and indoor environmental comfort of buildings. Several previous studies, including those by Marzouk and Othman [103], Ali et al. [104], Ding and Zhou [105], Buffat et al. [106]. Ahn and Sohn [107], Quan et al. [108], Fabbri et al. [109], Lilis et al. [110], Alhamwi et al. [111], and Ranalli and Alhamwi [112], have integrated GIS techniques in the development process of building energy models. Among these techniques, GIS-based models have proven to be the most powerful, owing to their strong capability to provide spatial representations of the real world for visualization and simulations. Additionally, GISs has been coupled with many developed energy models of buildings at different urban scales, as summarized in Table 2. Therefore, it is necessary to highlight the importance of GIS-based estimation approaches for promoting clean energy applications at the national and regional levels.

3. Methodology

The study methodology is based on the research objectives. Accordingly, all the relevant research efforts in the field of GISs-based rooftop PV potential estimation approaches (i.e., rooftop solar PV energy systems), were selected. These research papers are referred to as the "core literature", and three main criteria were proposed for the precise identification of the core literature, as reviewed in this paper. First, the literature must specify that the research effort (i.e., the research work) deals directly with GISs-based rooftop solar PV energy potential estimates. If the paper only discusses the potential of solar PVs on rooftops without relying on GISs-based assessment, it is excluded. Second, the research work must use one or more GISs-based estimation approaches, such as sampling, geostatistics, modeling, and machine learning approaches. If the paper only uses the GIS without a clear estimation approach, such as solar radiation mapping, it is excluded. Third, the research work must deal with solar radiation and rooftop characteristics, such as rooftop type, available rooftop areas, and tilted radiation. If the research work addresses topics such as buildings integrated with solar energy systems, it is not considered to be core literature.

Based on the above criteria, and as shown in Fig. 2, the study methodology involved five major steps as follows. 1) Keywords-based search of previous articles and related-abstracts was conducted utilizing ScienceDirect, Scopus, and Google Scholar. Rooftop photovoltaic mapping, rooftop photovoltaic assessment, rooftop solar photovoltaic estimation, rooftop solar PV potential geospatial assessment, and rooftop solar photovoltaic potential quantification are examples of the keywords used. 2) All articles were screened based on the aforementioned three criteria (e.g., the used approach must be GIS-based estimation approach; the article objective must be rooftop solar photovoltaic energy systems). 3) The articles cited by a paper that passed the screening test based on the above criteria were identified as additional candidate research in the review paper. 4) All articles selected in steps 1 and 2 were reviewed to identify the study scope, inputs, and used approach. 5) All review results were analyzed to determine the advantages and disadvantages of each approach, identify the research gap in the field of GISs-based rooftop PV energy potential estimates, and highlight future research opportunities.

Table 2
List of some existing building energy models developed through integration with geographic information systems.

The full name	Symbol	Description	Reference
Geographical UBAN Units Delimitation model	GUUD	Combination of GIS, parametric modeling, and solar dynamic analysis, and dividing the urban area into urban cells, classified solar producer and energy consumer	[113]
City Building Energy Saver	CityBES	A useful tool used to generate and simulate an urban building energy model using EnergyPlus, data of city buildings and energy conservation measures	[114]
City Geography Markup Language	CityGML	An open data model and XML-based format for storing and exchanging virtual 3D city models	[115,116]
Urban Modeling Design tool	UMI	A tool based on Rhinoceros, which allows the user to evaluate all of energy, daylighting, and walkability of urban neighborhoods	[117]
"3D Simulation of Urban Energy System"	SimStadt	It depends on 3D-city models, and supports energy transition planning in the urban scales	[118]
City Simulation	CitySim	Micro-Simulation of Resource Flows for Sustainable Urban	[119]

4. GISs-based estimation approaches

PV energy estimation approaches or PV energy prediction techniques are often referred to as "common methods/tools" for mapping, estimating, and evaluating the potential of PV system application in building structures, specifically rooftops and façades, through integration with a GIS. These approaches or techniques can be categorized as GIS-based machine learning approaches, GIS-based modeling approaches, including 3D GIS models (i.e., 2D/3D approach), GIS-based geostatistical approaches, and GIS-based sampling approaches. Each estimation approach integrated with a GIS has advantages and disadvantages in terms of performance and applicability in estimating and evaluating the potential of PV systems in building structures. GIS-based estimation models are typically constructed based on a range of datasets consisting of detailed non-geodata/geodata for the available solar radiation, building characteristics, weather, and the other related input variables. Then, the outputs of these inputs are utilized as a criterion/benchmark to assess the performance of the developed model and guide its algorithm design, as in machine learning algorithm-based models, i.e., data-driven based models. When the output falls within the required threshold, the corresponding analytical/estimation models are considered suitable for practical applications with a new input dataset.

In investigating the potential of deploying PV systems on rooftops, these approaches are integrated with the GISs to determine the 1) physical potential, i.e., the total amount of received solar energy that reaches the target building rooftops; 2) urban potential, i.e., the available areas on building rooftops that should be suitable for installing PV panels; 3) technical potential, i.e., the estimated total electrical energy received from the suitable rooftop areas on buildings, considering the technical characteristics of the PVs, such as, their efficiency, capacity, Stability, and performance [120–122]; 4) social-economic potential [123–125]; and 5) environmental impact. This means that GISs-based rooftop PV potential estimates are a hierarchical methodology that begins with assessing the abundance of solar radiation and then proceeds to determining the available and suitable surfaces for the rooftops down to the environmental impact assessment. This section provides a comprehensive review of the GISs-based estimation approaches used for building rooftops at different urban scales to highlight the importance of GIS integration with estimation approaches in supporting and planning an urban PV system infrastructure.

4.1. Sampling approaches

Sampling approaches are extrapolation techniques aimed at determining the potential for PV energy systems on rooftops at different urban scales. Usually, the basic principle of sampling approaches is to calculate a variable (or variables) of interest solely to a selected sample from points or sites and then utilize an appropriate strategy to extrapolate the variable(s) for the entire area or entire dataset. This allows researchers to obtain reliable estimates of the variable (rather than the assumed constant-coefficient), while keeping the computational

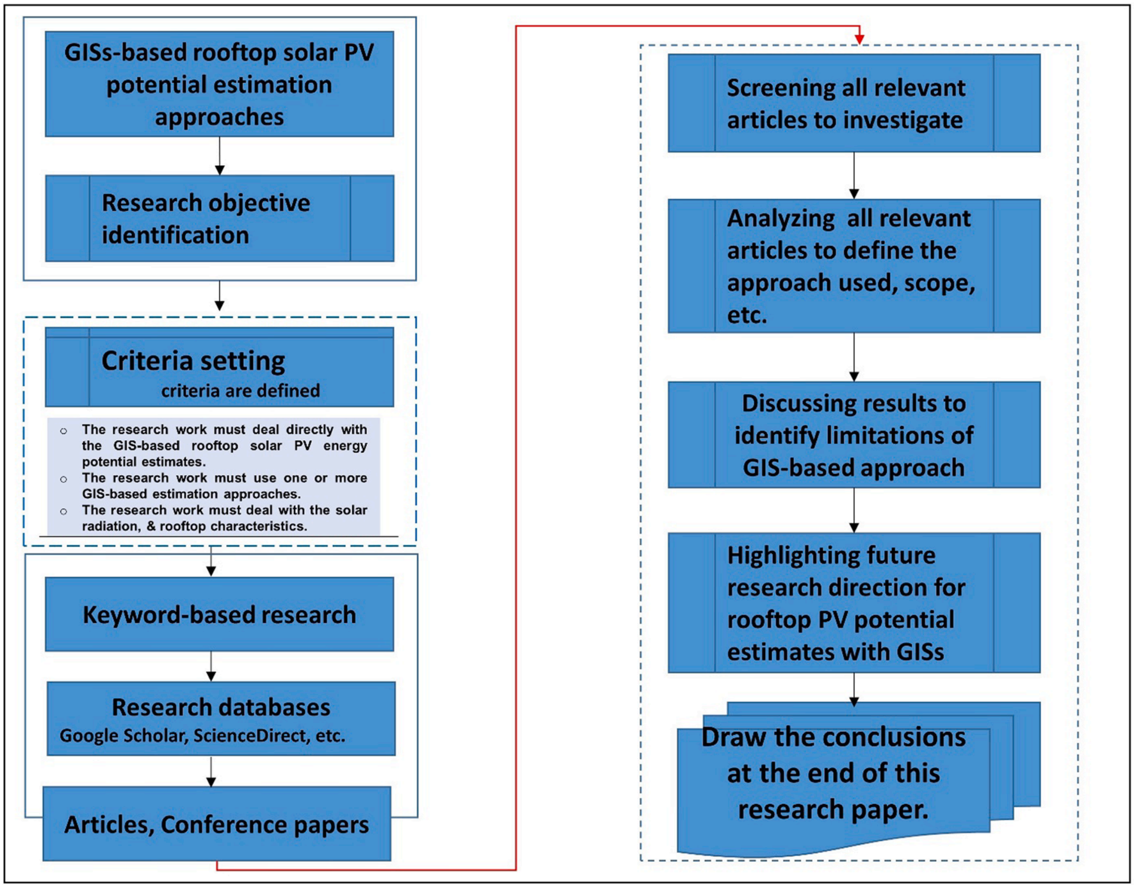

Fig. 2. Flowchart of the review methodology.

requirements of the method reasonably low. Although the use of a constant coefficient is still common in some sampling approaches, however, it is no longer assumed and should be dependent on a comprehensive analysis of samples. While this approach is theoretically usable for any type of variant, it has been utilized primarily in large regional settings to estimate the available rooftop area. Based on considerations of the available data and study area scale, sampling approaches can be divided as a simple sampling, multivariate sampling, and a complete census approaches. The simple sampling approach provides an estimate of the available rooftop area for the selected area; the estimate is then extrapolated to the entire target area (study area). The multivariate sampling approach draws a relationship between the available rooftop area and the population density. The complete census approach is based on calculating the entire rooftop area for the study area. This can be performed using existing statistical data for the building information, including the number of buildings, floors, and floor areas or by using advanced cartographic datasets and/or GIS applications. Applications of the sampling approaches in the field of rooftop solar PV potential estimates are summarized in Table 3.

At the core of any approach, two major steps that must be taken to obtain accurate estimates of the potential of PV systems on urban building rooftops. The first is to calculate the total area available on the rooftops, and the second is to determine the suitable rooftop areas for PV panel installation. In this context, Izquierdo et al. [126] classified Spanish municipalities according to their available rooftop areas for PV installations based on relevant density data for both buildings and population; the classes were expressed on a scale from “low density” to “very high density”. During the classification process, a representative building typology was assigned to each municipally, according to two key parameters: building density and population density. The ratios of the different total available areas for each representative building typology were calculated depending on the building samples for each class/typology. In each sample, a GIS vector dataset was utilized to calculate the ratios and different steps were followed to verify sample quality, including the calculation of a sample coefficient of variation. In addition, an error term was calculated to measure the uncertainty of the sample strategy for each typology. The ratios were then extrapolated for all municipalities in Spain. The results showed that the total available area was approximately 571 km^2 across the country. This was followed by another study by Izquierdo et al. [54], who adopted the same approach to estimate the potential for rooftop PV energy generation in buildings in Spain. The results showed that PV systems could satisfy nearly 4% of the overall electrical energy demand in Spain. Schallenberg-Rodriguez [33] used the total roof area and a related utilization factor according to each municipality. They found that the total available roof area is 87.6 km^2, of which 43.4 km^2 is suitable for installing PVs in buildings in the Canary Islands; this would be sufficient to satisfy nearly 9,000 GWh of the electrical energy demand. Likewise, Byrne et al. [34] used the same strategy to evaluate the rooftop PV potential in Seoul. The results showed that the rooftop area suitable for PV installation is 89,544,961 m^2, which can provide 30% of the total annual electrical energy consumption for Seoul.

Regardless of the nature of the sampling approach used, an adequate extrapolation strategy combined with GIS techniques is the primary key for extrapolating and evaluating a target area. In this regard, Groppi et al. [127] presented the concept of “urban cell” for evaluating suitable available rooftops for PV installation. They used factors related to the rooftops, such as the slope, rooftop orientation, and annual received solar radiation to classify buildings in Ladispoli, Italy. An ArcGIS technique was used to extrapolate the four aforementioned factors; it was excluded; the pitched rooftops in the 25°-40° range, and the rooftops with an annual average solar irradiation rate of less than 1200 kWh per

Table 3
Results of solar photovoltaic potential estimates on rooftops using sampling approaches according to the literature reviewed.

Type of building	Scale	Approach	Inputs	Key finding	Reference
Multiple	Municipality/ District	Sample	Total roofs of building; the related utilization factor for each municipality	87.6 km^2 (total roof area) 43.4 km^2 (suitable roof area for PV installation)	Schallenberg-Rodriguez [33]
Multiple	City	Complete census	No. of buildings; total area of buildings; floor area	(89,544,961 m^2) suitable roof area for PV installations	Byrne et al. [34]
Multiple	National	Multivariate sampling	Building density; population; density; GIS data	571 km^2 of Spain buildings is the available areas	Izquierdo et al. [126]
Residential	Two city districts	Complete census	Rooftops, slope; rooftop orientation, the annual received solar radiation	“Urban cell” is a suitable method to assess the usable solar photovoltaic energy potential in different urban contexts	Groppi et al. [127]
Industrial and commercial	City	Complete census	OpenStreetMap (OSM) building footprint database layers	20,939,982 m^2 (footprint area) 1164 m^2 (mean rooftop area)	Horan et al. [128]
Residential and commercial	A city district	Complete census	satellite imagery for rooftop areas	12.24 MW of electrical energy produced when installing high-efficiency PV panels	Khan and Arsalan [129]
Multiple	25 cities	Complete census	PV-Geographical dataset (reference location data); longitude; latitude; altitude	The estimated error is between 4% and 6% for 90% of photovoltaic electrical energy estimates	Bocca et al. [130]
Multiple	City	Complete census	Municipal geographical data; Aerial images for rooftops	33% of building rooftops is appropriate areas for installing PV panels	Nguyen and Pearce [131]
Multiple	City	Multivariate sampling	GIS data: population; rooftop areas	The relationship between total rooftop area and population over the studied area is 70 m^2 per capita ± 6%	Wiginton et al. [132]
Multiple	City	Complete census	orthoimagery and DSM data	The value of the correlation coefficient between extracted rooftop area and manual digitized reference data is up to 0.9	Mallinis et al. [133]
Multiple	National	Complete census	GIS data; satellite imagery	32% of national electrical energy demand	Vardimon [134]
Residential	City	Sample	129 representative building rooftops	The solar utilisation rooftop factor is between 25% and 50% of the examined rooftop cases	Karteris et al. [135]
Multiple	City	Complete census	LiDAR data; rooftop prints; aerial images	High performance methodology with accurate results by 95%	Nguyen at al. [136]
Multiple	City	Complete census	land use map; aerial data	40% of electrical energy production for 2008; 2300 km^2 of available rooftop area	Liu et al. [137]
Multiple	City	Complete census	satellite imagery: landuse; solar radiation	40% of local electrical energy demand	Guangxu et al. [138]
Residential	City	Multivariate sampling	Statistical dataset: population; rooftop areas	265.52 km^2 of rooftop areas; 79.89% of energy needs can be provided	Ordonez et al. [139]
Multiple	City	Sample	Aerial image: the used PV areas; irradiance	Approximately 56% of electrical energy demands can be satisfied	Yuan et al. [140]
Educational buildings	A city district	Sample	satellite imagery of rooftops; weather data	Utilization factor is a significant way to estimate the potential of solar PV for rooftops	Thai and Brouwer [141]

m^2, and an area of less of less than 2.5 m^2. Horan et al. [128] employed the “OpenStreetMap” building footprint dataset to determine the surfaces of industrial and commercial buildings in Dublin, Ireland; the QGIS tool was adopted for this purpose. They estimated the building footprint area to be 20,939,982 m^2, with an average of 1,164 m^2 of available rooftop area per building; thus was potential to produce between 855,490 and 1,069,363 kW of energy. Khan and Arsalan [129] used satellite images to determine the available area for PV installation in buildings in Karachi, Pakistan. The relationship between the total rooftop areas and population was estimated to be 13 m^2 per capita, ± 5%. The results showed a potential energy production equivalent to 12.24 MW with the installation of high-efficiency PV panels. Bocca et al. [130] introduced a simple sampling strategy for estimating the PV potential in a large region when only a few scattered measurement points are available. Nguyen and Pearce [131] utilized aerial images to extract appropriate areas of building rooftops in Kingston for installing PV panels. In some case, pitched rooftops were removed. Ultimately, the authors found that 33% of the rooftop areas is appropriate for PV installation. Wiginton et al. [132] integrated a GIS with an object-specific-image-recognition technique to define the available areas of building rooftops in Ontario, Canada for PV system installation. Extrapolation was performed utilizing the rooftop area-population relationship, where was estimated at 70 m^2 per capita, ± 6%, with a potential annual electrical energy production of 6,909 GWh (nearly 30% of Ontario’s electrical energy demand).

A set of different sources of uncertainty associated with solar PV potential estimation has been addressed either through scenario-based analysis or via sensitivity analysis. Izquierdo et al. [126] provided the uncertainty statistical propagation, which focuses only on the available rooftop area for PV installations to determine the estimation errors. Bocca et al. [130] compared the predicted outcomes with the PVGIS data obtained by the European Commission Joint Research Centre. Schallenberg-Rodriguez [33] used sensitivity analysis to investigate the importance of technical variables (i.e., PV cell type and installation characteristics on usable rooftops) and their influence on the potential estimates of PV energy production. Nguyen et al. [131] also used sensitivity analysis and focused on the total surface areas of installed PV panels as a function of rooftop PV potential estimation. Mallinis et al. [133] integrated the dataset of a geospatial vector with remote sensing data for targeted buildings in Thessaloniki to minimize uncertainties, whereas Karteris et al. [135] used statistical analysis, which focussed on the rooftop’s orientation to address uncertainties. Concludely, sampling approaches can be extremely useful for extracting the rooftop characteristics of an area of interest [133,134], without the need for a large dataset or excessive calculational power.

4.2. Geostatistical approaches

Geostatistical approaches are a robust and well-established family of GIS-based estimation methods that utilized to perform spatial statistical analyses and to predict the parameter values relevant to spatial phenomena [142]. For example, they can be used to predict the distribution of solar radiation; the spatial coordinates of the data are incorporated into the analyses. As a result, several geostatistical estimation methods were originally developed as a practical expedience, i.e., for describing the spatial patterns and interpolation values of locations that had not been sampled. These methods have evolved to provide interpolated values and uncertainty measures for these values. On this basis, geostatistical estimation approaches have been broadly used with environmental data, including solar irradiance and solar energy data. In estimating the PV potential, geostatistical methods play a major role in the spatial interpolation of the horizontal solar radiation, which, in turn, generates maps of solar radiation in urban areas. These maps are essential tools for defining the potential of urban areas for deploying/ implementing PV panel technologies linked to building structures, including rooftops. This step is often called the determination of the physical potential and aims to assess the rooftop solar radiation available in different urban environments (a fundamental pillar for investments in PV energy systems).

In general, the working principle of geostatistical methods is based on the consideration of spatial points as single realizations of a random variable of interest Z, such as solar radiation. It is considered that Z has a deterministic part and a probabilistic part, as shown in Eq. (1) [143].

Table 4
Results of the solar photovoltaic potential estimation on rooftops using geostatistical approaches according to the literature reviewed.

Type of building	Scale	Approach	Inputs	Key finding	Reference
Multiple	National	Kriging	Geographical and meteorological data, such as altitude and temperature; site characteristics	By utilizing the GIS-based optimisation model, the decision-makers can easily and accurately predict the total electrical energy production from the SPV energy systems applied to building rooftops	Hong et al. [147]
Multiple	National	CoKriging	The weather data; satellite imagery	Cokriging is a promising technique for mapping global solar radiation	D'Agostino and Zelenka. [148]
Multiple	County	Ordinary & residential Kriging	Daily measured values at surfaces for solar radiation between 2003 and 2006	Both methods provided the same estimates in summer, however, the residual kriging method is more suitable when mapping the solar radiation in complex terrain areas	Alsamamra et al. [149]
Multiple	National	Ordinary kriging	Daily solar; temperature; measured values at surfaces for precipitation for years 2005–2008	Daily solar irradiation map across Spain with 1-km spatial resolution	Moreno et al. [150]
Multiple	National	Kriging, Cokriging, BIN, INDW, RBFM	Weather data; monthly temperature; precipitation; humidity; sunshine hours	Strong correlation between the estimated and observed values of solar radiation ($R^2 = 0.86$)	Fathizad et al. [151]
Residential	1500 representative buildings	Ordinary kriging	Weather parameters; factors related to density and efficiency of photovoltaic systems;	The precision of derived-solar-irradiation data relies on a number of factors related to the density and efficiency of the PV systems, and the climatic conditions	Bertrand et al. [152]
Educational building	National	Kriging	Educational facility data; photovoltaic panel data	Investigation of the effect of both technical, economic, and political aspects on the net zero energy solar buildings	Koo et al. [153]
Multiple	National	Spline	Monthly measured data for the horizontal and tilted of solar radiation; temperature; humidity; wind direction; sky factor; location	SPV potential across Canada was mapped with nearly 10 km resolution	McKenney et al. [154]
Multiple	National	Kriging	Solar radiation intensity; wind speed; air temperature; system conversion data; etc	200 kWh/m^2 of the expected electrical energy production in northwestern and northern regions, and 130 kWh/m^2 in southwest regions	Wang et al. [155]
Multiple	National	Kriging, Variogram	Solar radiation data	Mean error of the solar radiation was between 0.5% and 1.7%	Rehman and Ghori [156]
AN	National	Kriging	Geographical data: longitude; altitude; latitude; weather data: relative humidity; temperature; sunshine; radiation; wind speed	Developed map of MADSR is useful tool for estimating unmeasured sites and determining optimal sites for installing PV systems	Lee et al. [157]
Multiple	13 districts	AN	Satellite imagery to determine rooftop areas; georeferenced solar radiation map	58% of rooftop areas receives more than 4 kWh per square meters of solar radiation during the year	Mishra et al. [158]
Residential and commercial	City	AN	Satellite imagery; elevation data (Digital Surface Model and Digital Elevation model); Weather data; building footprint data	239,833 building rooftops are appropriate for installing the rooftop SPV panels	Wong et al. [159]
Multiple	County	AN	Weather data; geographic data; solar radiation data	Producing the equivalent of 38,693 GWh/year of electricity when applied PVs	Carrion et al. [164]
Residential	City	AN	LiDAR data; rooftop vectors; historical radiation data	The representation of the estimated global radiation on each building offers new possibilities in using renewable sources and changes the conception of rooftops to a potential source of PV energy	Quiros et al. [165]
Residential and commercial	province	Map algebra ; Spatial analytic	GlobCover-2009-land-cover-products to extract the built areas; georeferenced solar radiation map	SPV technology offers high potential for rooftop installations and large scale PV plants	Sun et al. [166]
Multiple	National	Geospatial analysis/(PVGIS)	Cartographical dataset to extract rooftops; Solar radiance map	A sustainable, emission-free electricity system is possible at a cost lower than the current market price, providing 40% of energy needs	Gomez-Exposito et al. [167]
Multiple	City	GIS-based spatial algorithm	Energy resource map; Satellite imagery for city rooftop areas	Approximately 29% of energy demands can be satisfied	Porse et al. [168]
Residential	City	Spatially constrained multivariate clustering	Satellite imagery; No. of suited households for PVs	400 MW of solar energy can be aggregated on residential rooftops	Lopez-Ruiz et al. [169]

Note: The input variables refer to the input data used, whereas AN means that the approach used was not precisely defined by the authors (only geospatial analytic).

$$Z(x) = M(x) + S(x) \tag{1}$$

Here, $(x) = (x, y)$ is a 2D site vector, $M(x)$ is the deterministic part, the average of $Z(x)$ and $S(x)$ is the probabilistic part. Geostatistical predictions are typically performed based on a classical family of linear models called kriging models [143]. Kriging interpolation encompasses a variety of spatial prediction methods, including ordinary, simple, universal, probability, disjunctive, empirical methods, whose appropriateness for rooftop PV estimates at different large urban scales depends on the data characteristics and desired spatial model. The kriging principle assumes the probabilistic behavior of a random field, in which one can extract possible realizations of the field that corresponds to the data. In other words, kriging assumes that the direction or distance between spatial points reflects a spatial correlation that can be employed to explore variance at a specific surface. The interpolation is performed utilizing a local probabilistic weighted average of known neighborhood points to obtain spatial predictions for a new point(x_0), as shown in Eq. (2) [144].

$$\widehat{Z}(x_0) = \sum_{i=1}^{N} w_i(x_0) Z(x_i) + w_0(x_0) \tag{2}$$

In the equation above, w_i is a kriging weights (unknown weight for measured value at the i location), N is number of measured values (points), x_i is a measured neighborhood point. If the number of measured values (N) is sufficiently large, a local neighborhood can be utilized after being selected based on suitable knowledge or a k-nearest neighbor model. Additional details regarding geostatistical analytical techniques and kriging methods can be found in [142,144–146].

As mentioned previously, kriging methods play an important role in the estimation of the PV potential at different urban scales, as summarized in Table 4. For example, Hong et al. [147] used a kriging method to optimize a map of projected/expected electrical energy production for rooftop PV systems in South Korean cities. They justified the use of kriging as a useful technique for determining the overall direction/trend of a given area, as well as for reflecting the spatial correlation between the measured values. D'Agostino and Zelenka [148] employed the Cokriging (an extension of the kriging method) method with observation data obtained from a Swiss meteorological network to predict the daily solar radiation in Switzerland. The daily solar radiation predictions were validated using satellite imagery estimates and it was found that the coKriging method reduced prediction errors (RMSE) to approximately 2.5 MJ m^{-2}. Alsamamra et al. [149] compared the performance of residual and ordinary kriging methods when mapping the monthly average of solar radiation in Andalusia, Spain. They concluded that the residual kriging method could provide high-resolution results when mapping the solar radiation in complex terrain areas. Likewise, Moreno et al. [150] compared the performance of ordinary kriging with an ANN when estimating the daily global solar irradiation in Spain. The results demonstrated the ANN outperformed with an error of 2.33 MJ m^{-2} day^{-1}. Fathizad et al. [151] employed eight geostatistical methods, including kriging, cokriging, and radial basis function methods, to evaluate the spatial correlations between solar radiation data along the territories of Iranian cities. The results showed that the radial basis function method was the most effective method, with R^2 value of 0.972 and RMSE of 0.39%.

Furthermore, Bertrand et al. [152] used ordinary kriging to calculate the daily solar irradiation distribution in Belgium by considering 1,500 representative residential PV installations. They concluded that an accurate estimation of the derived solar irradiation relies on the factors related to weather, density and the efficiency of PV systems. Koo et al. [153] developed a spatial footprint-based on the kriging method and were able to estimate the energy self-adequacy rates at unmeasured points. The authors observed that the energy self-adequacy rates at the unmeasured points could be estimated based on values measured at the target urban locations. In addition, Besides, McKenney et al. [154] in Canada, Wang et al. [155] in China, Rehman and Ghori [156] in Saudi Arabia, and Lee et al. [157] in South Korea used kriging methods to investigate the solar energy potential. Wang et al. [155] reported an expected generation of the equivalent of 200 and 130 kWh of electrical energy per square meter in the northwestern and northern regions, and the southwest region, respectively. They also concluded that by using the spatial analytical technique (kriging) of GIS, the distribution intensity of the solar radiation and PV potential in different regions of China, could be determined.

Geostatistics have not been limited to kriging methods; rather, they have been used with several other spatial-statistical analytical methods. Mishra et al. [158] studied the rooftop-based solar energy potential in in thirteen districts of Uttarakhand, India, utilizing a remote sensing and GIS technique; they used statistical clustering to calculate the available areas of rooftops. They found that 58% of the rooftop areas receives more than 4 kWh per m^2 of solar radiation during the year and could generate 57% of the electrical energy consumption in Uttarakhand. Likewise, Wong et al. [159] used a decision tree-based classification method [160] combined with a convolution kernel to classify and identify suitable rooftop areas for PV panel installation in buildings in Hong Kong. The results showed that 239,833 buildings (out of 309,606) were appropriate for PV panel installations. Aydin et al. [161] employed a GIS-based Fuzzy membership method to determine appropriate locations for the installation of hybrid wind-solar-PV energy systems in the western part of Turkey. Amjad and Shah [162] employed the density-based-clustering to determine and aggregate sites with considerable potential for solar energy generation in Pakistan. Zhang et al. [163] used a spatially constrained analysis technique to analyze and estimate the spatial–temporal distribution of the solar energy potential in China. Carrion et al. [164] employed a GIS-based spatial-statistic approach to determine the most appropriate sites for PV panel installation in Andalusia. The results showed that nearly 38,693 GWh/year of electrical energy could be produced by PV systems. Quiros et al. [165] used a solar radiation analysis tool (spatial analyst tool) in a GIS framework to map the rooftop-solar energy potential in Caceres, Spain. Sun et al. [166] also employed GIS spatial analysis functions to evaluate the geographic and technical potential and the economic feasibility of PV electrical energy generation in Fujian Province, China. They found that the PV technology showed significant potential for use in rooftop installations and large scale PV plants. Uncertainties associated with potential estimates of solar PVs are identified using different methods. Alsamamra et al. [149] used linear regression analysis to investigate the effect of both elevation and sky view factors on the solar energy received. Amjad and Shah [162] used density-based clustering, which focuses only on high-irradiance surfaces suitable for solar installations. Wang et al. [155] developed a novel method based on existed data to evaluate the effects of both conversion efficiency and solar irradiance intensity on the distributed PV potential. Bertrand et al. [152], Hong et al. [147] and Sun et al. [166], all used sensitivity analysis (includes correlation analysis) to investigate the relative effects of input variables (e.g., the latitude, temperature, and density of rooftop PV systems) on the potential of PV electrical energy estimates.

4.3. Modeling approaches

Physical approaches, i.e., white box-based methods, are similar to the types of rooftop analyses mentioned above; physical GIS-based approaches usually involve developing 3D models to estimate the PV energy an received solar energy, as well as to simulate the effects of shade and trees on the potential of a building's structure, including the rooftop and façade (with varying data and tools for developing those models). The key point in this type of GIS-based estimation approach is that the decision related to a suitable rooftop for installing PV panels is not made based on a constant value or by manually defining building rooftops. Instead, the ideal values for the characteristics of building rooftops are only entered into the computer model, and then the GIS program identifies the most suitable areas. GISs can compute the related important variables automatically, such as the slope and azimuth of the rooftop, rooftop shape, and footprint area. This results in a faster, more objective, and more accurate approach for determining the availability of suitable rooftops.

Concerning 3D models are often constructed from high-resolution images (i.e., orthophotagraphies) or LiDAR (i.e., light detection and ranging/3D representative) data and incorporate with slope, orientation, and building structure data to evaluate the overall PV energy electrical generation potential [143,170]. LiDAR is one of the most popular remote-sensing techniques, which is allowed taking a sample for the earth accessible surface in the shape of a gird of high-resolution elevation points. As a result, LiDAR data have become more widely available at higher resolutions, and their use has become highly desirable for estimating rooftop area. In particular, LiDAR data can be integrated with a GIS to establish a robust approach for rooftop PV potential estimates [171]. Several investigation studies have been conducted on rooftop PV potential at different scales. Table 5 presents previous studies in the field of PV potential estimation on building rooftops according to the reviewed literature.

Hofierka and Kanuk [172] utilized a 3D city model generated in a GIS together with a PVGIS radiation tool [173] to assess the PV energy production potential from the rooftops of Bardejov buildings in eastern Slovakia. They found a high rooftop PV energy potential, potentially coving approximately two-thirds of the total current electrical energy demand of Bardejov. Jo and Otanicar [174] presented a new methodology for incorporating remote-sensed image data with a GIS to evaluate both the capacity and the benefits of installing PV energy systems on building rooftops in Chandler, Arizona. The results showed that installing solar PV systems on the target buildings could produce approximately 18,600 MWh/year, corresponding to 10% of the current electrical energy consumption. In a follow-up analysis, Kingston, Nguyen and Pearce [175] studied the effects of shadows on the rooftops of 100 buildings using the GRASS r.sun tool [176]. Rooftops with a southeast-through-southwest-facing-aspect i.e., 90-to-270° and a slope within 15° of the local latitude, were considered suitable for PV installation. The results were validated based on one building rooftop, on which the shadows measured during the morning and evening hours for comparison with the modeling results. Brito et al. [177] conducted an assessment of the rooftop PV potential of 583 buildings, based on LiDAR data. A filtering method was used to identify rooftops without shadows and determine the most suitable slope. The solar radiation was also calculated using the solar analytical extension for ArcGIS. The assessment results showed that approximately 11.5 GWh/year of electrical energy could be obtained, which could cover approximately 48% of the local energy demands of buildings. Strzalka et al. [178] used a 3D city model and a shading algorithm to investigate the deployment potential of a PV energy system in Ostfildern, Germany and to analyze the impact of shadows on the solar radiation potential. The investigation results were compared with actual energy-consumption values to determine the consumption rates of the target buildings. They observed that 3% of the rooftop areas of buildings were partially shaded and that 35% of the local electrical energy demand of buildings in Ostfildern could be satisfied by rooftop PV systems.

The estimation of PV energy potential for building rooftops is a complex task, as it requires a wide range of parameters and considerable experience, which, in turn, depend on the morphology and distribution of buildings in different urban environments. However, several investigation models have been developed with integrated GIS and LiDAR datasets to extract and evaluate the potential of building rooftops at various urban levels. To obtain a suitable estimation of a building's rooftop shape, Boz et al. [179] used footprints of buildings in Philadelphia, USA and LIDAR datasets in conjunction with a GIS technique to extract the rooftop shapes of buildings. The rooftop classification was based on the aspect and slope of the building rooftops, and a rooftop polygon was created over the building footprints according to the classes; the shadow values were also calculated. It was found that 48.6% of the rooftops were appropriate for PV installation. Gooding et al. [180] introduced a modeling method that used low-resolution LiDAR data and building footprints to extract the best shapes of rooftops, based on a catalog of common rooftop shapes for 705 buildings in Leeds, UK. The method was validated using a 169 ground-based survey and 536 aerial photographs; it was found that the method could determine the final rooftop shapes with an accuracy of 87% and an error of 3.76°. Huang et al. [181] presented an object-based-approach to extract the most appropriate rooftop sites for installing PV panels on the rooftops of buildings in Lujiazui, Shanghai, China, using LiDAR data. The effect of the 3D urban morphology on the variance of the solar radiation was analyzed, and the results were collected to form a list of appropriate rooftops. Likewise, Latif et al. [182] merged LiDAR with a GIS technique to identify the most suitable sites for installing PV panels in buildings in George Town, northern Malaysia. Five key criteria were considered-a layer for high solar radiation, and thresholds for slopes, aspects, the ground, and humans. The results showed that the rooftops with slopes of 30° were the most suitable sites for installing PV panels, whereas rooftops with slopes of 15° were the least suitable. Lukac et al. [183] proposed a new methodology for defining a rating list for rooftop surfaces within urban areas in relation to their solar potential and suitability for installing PV energy systems. Sreckovic et al. [184] suggested considering higher energy generation and the corresponded benefits simultaneously when determining suitable rooftop areas of buildings for PV installation.

However, previous research efforts went beyond determining the most appropriate location for installing PV energy systems on building rooftops; studies also focused on many important aspects of rooftop PV energy systems (i.e., the effects of factors related to shadows, slopes, and available radiation; assessment of physical, urban, technical, and economical potentials) to encourage the use of PV technologies and to reduce energy-related emissions affecting urban environments and human health. Bill et al. [185] developed a 3D model for analyzing the potential for solar energy generation in building structures, including rooftops, façades, and ground surfaces. Choi et al. [186] proposed the development of a PV analytical model based on a coupling between ArcGIS and "TRNSYS" to assess the distribution potential of PV energy systems in urban areas more effectively by considering the overall usable rooftop areas, PV panel performance, and corresponding electricity production. Verso et al. [187] developed a model that focuses on identifying the possible differences between two types of rooftop typologies. First, the PV panels were placed parallel to the rooftop, and the hourly solar radiation was calculated based on the factors related to the shading, orientation, and slope of the rooftop. Second, the structures were mounted in the optimal positions while considering the shadow factor. Mavromatidis et al. [188] introduced a modeling framework considering buildings, available rooftop areas, rooftop orientations, costs, and surrounding topographies, to identify the amount of solar radiation potential and available areas for installing PV resources in residential buildings in Zernez, Switzerland. Likewise, Tooke et al. [189] presented an analytical method for identifying the diurnal and seasonal effects of trees on the received solar radiation on residential building rooftops in Vancouver, and found that trees reduce approximately 38% of the total solar radiation received by residential rooftops.

Furthermore, several previous research efforts [190–197] have addressed the estimation of the solar radiation received by building rooftops using their methodologies. Kodysh et al. [193] developed a modeling methodology using LiDAR data and a GIS approach to estimate the rooftop solar potential of 212,000 buildings in Knox County, Tennessee, USA. The methodology considers input variables, such as the direction of rooftops, shadowing factors, elevation/height, and related atmospheric conditions that affect the solar radiation density on land surfaces. The authors concluded that the methodology was an effective in estimating the solar radiation on the rooftops of multiple buildings. Machete et al. [77] used a 3D-GIS model to analyze the effects of the

Table 5
Investigation results of the potential of solar photovoltaic systems on rooftops at different urban scales using GISs-based models.

Type of building	Scale	Total area of buildings	Suitable total rooftop area for SPV installation	Key finding	Reference
Residential and industrial	134 municipalities	–	43 square km	343, 719, 858 GWh/yr	Bergamasco and Asinari [53]
Multiple	Small City	513,000 m^2	303,000 (30.3 ha)	Approximately 45% of the current annual electrical energy use	Hofierka and Kanuk [172]
Commercial and office buildings	932 buildings	120,000 m^2	36,000 m^2 (30% of total building areas)	10% of the overall electrical energy demand	Jo and Otanicar [174]
Residential and commercial	100 buildings	40,000 m^2	22,000	R.sun. Grass GIS has high strength to work with different levels of complex surfaces	Nguyen and Pearce [175]
Multiple	City	133,200 m^2	–	The presented method is a useful tool for assessing urban PV resources	Nguyen and Pearce [176]
Residential	583 buildings	85,000 m^2	–	48% of the electrical energy demand	Brito et al. [177]
Residential and commercial	Town	1,500,000 m^2	1688 m^2	35% the overall building electrical energy consumption	Strzalka et al. [178]
Multiple	City	33.7% (of building areas)	48.6% (suitable rooftop areas)	The developed model has a high capacity to extract rooftop parts across the urban area	Boz et al. [179]
Multiple	A city district	3,000,000 m^2	–	The objective-based approach is an effective method to determine the suitable rooftops for solar energy utilization potential	Huang et al. [181]
Residential	Village	25,200 m^2	8640 m^2	34% of annual electricity use/1370 kWh/m^2 (5,248,500 kWh)	Mavromatidis et al. [188]
Residential	City	Areas of 4,460 houses	Areas of 4460 houses	Production capacity covers 31,000 buildings (190,000 MWh/yr)	Carl [199]
Multiple	157,724 buildings	700,000,000 m^2	–	56% of electrical energy demand	Rodriguez et al. [200]
Multiple	Municipality	3 buildings	Rooftop areas of 3 buildings	5294 MWH (14% of total electrical energy demand)	Guen et al. [201]
Multiple	9718 buildings	–	–	53,061 MWh/yea	Jo et al. [203]
Educational buildings	13 buildings	–	65% of the overall building rooftops	19% of the overall electrical energy demand	Chow et al. [204]
Residential	811 buildings	–	–	25% of the building energy demand	Santos et al. [206]
Residential, industrial, administrative	17,392 buildings	17,660,000 m^2 (17.66 km^2)	1,350,000 m^2 (135 ha)	247–345 GWh of the annual electrical energy consumption	Saadaoui et al. [207]
Educational buildings	19 buildings	23,730 m^2	8,572 m^2	300,269 kWh	Song and Choi [208]
Multiple	1071 rooftops	–	–	700 kWh/m^2	Jochem et al. [209]
Multiple	National	41,285,000,000 m^2 (41,285 km^2)	485,360,000 m^2 (48,536 ha)	48.6, 53.2, 58.8 TWh according to three scenarios	Buffat et al. [210]
Multiple	26.9 million buildings	7.7 billion m^2 (23% of US buildings)	32% (nearly 2.5 billion m^2 is suitable rooftop areas)	Ranging from 16% to 88% of the rated electrical energy consumption	Margolis et al. [211]
Residential and commercial	City	190,232 m^2	89,782 m^2	4,500 MJ/m^2/yr of solar energy can be obtained by 20 of rooftop areas	Li et al. [213]
Multiple	City	Areas of 1000 buildings	–	68% kWh/m^2/yr	Biljecki et al. [214]
Residential and commercial	1700 buildings	660,000 m^2	400,000 m^2	5% to 10% of reductions in the received solar irradiance in next 10 and 20 years, respectively	Hafeez [218]
Multiple	National	8,266,725 m^2	7,895,068 m^2	15,423.75 GWh	Ko et al. [219]
Residential	A city district	0.83 km^2	–	The GIS-based proposed model is a useful tool to define the suitable areas for PV installations	Aboushal [220]
Multiple	A city district	–	4,964,118 m^2	1,130,371 MWh	Hong et al. [222]
Multiple	Regional	–	49–64% of EU building rooftops	680 TWh (24.4% of the current demand)	Bodis et al. [223]
Multiple	City	458.27 Km^2	–	12.8 to 20% of the mean daily energy demand	Singh and Banerjee [224]
Residential	360 buildings	1.11 Km^2	–	500 kWh/m_2 (low houses) 30 kWh/m_2 (high houses)	Vulkan et al. [225]
Residential	County	74,859 Km^2	–	178.6 GWh/yr of electrical energy	Hafeznia et al. [226]
Multiple	City	10.554 Km^2	134.282 Km^2	779,154,752 kWh/yr	Jamal et al. [227]
Multiple	City	18.5 Km^2	17,000 rooftops	3.6 to 5.3% of electrical energy	Jakubiec and Reinhart [228]
Multiple	743 buildings	809,837 m^2	678,805 m^2	63.78 GWh/yr ~ 93.97 kWh/m^2/yr	Song et al. [229]
Residential and Industrial	City	257 km^2	14.12 km^2	796 GWh of electrical energy production	Dehwah et al. [231]
Residential and Industrial	Municipal and National	–	504 km^2	In Sweden, 540 km^2 is the total usable rooftop areas with an installed capacity of 65–84 GWp	Yang et al. [233]
Multiple	3 cities	0.1 km^2; 0.12 km^2; 0.45 km^2	0.1 km^2; 0.12 km^2; 0.45 km^2	The proposed method is most suitable in urban environments for estimating the fixed optimum slope of PV arrays compared with other methods	Lukac et al. [234]
Multiple	City	292.54 km^2	1.46 km^2	Installing 850 MWp of rooftop PV systems with a reduction of 30% of emissions related to the use of electrical energy	Jurasz et al. [235]

urban context on the solar energy potential of Lisbon buildings in Portugal. Many simulations of solar energy potential were performed at various levels of detail for the surrounding urban context (i.e., with and without). The authors found a mean difference of 30% in the studied cases with and without. Saratta et al. [198] integrated 3D urban models for buildings and facades with GIS environments to evaluate the potential of PV technology for retrofitting building facades in Ticino, Switzerland. Additionally, other studies [202,205,212,215–217,221,230,232] have covered several aspects of PV power applications, e.g., those related to the physical potential (received solar radiation), rooftop potential (available area), technical potential (amount of energy generation) and economical potential. Uncertainties in the potential estimates of rooftop PV were also considered. Suri and Hofierka [173] applied a cross-validation technique with terrain data optimized by the multivariate interpolation tool in GISs to improve the solar radiation estimation in terms of prediction errors of the model and model output spatial patterns. Carl [199] used the linear regression statistical uncertainty, which focused on elevation, slope, lot size, and rooftop area, for PV potential estimates. Rodriguez et al. [200] compared the results both of 3D CityGML urban data model called LOD1 (which considers that all rooftops are flat) with another 3D CityGML urban data model called LOD2 (which considers that all rooftop structures are tilted) when applied in each municipality to investigate the uncertainties of rooftop PV potential. Lukac et al. [202] applied a classified-georeferenced-LiDAR point [209], which focuses on rooftops for the PV estimates of buildings. Thebault et al. [217] provided an ELECTRE-TRI method to address the uncertainty issues related to the urban context on PV estimations.

4.4. Machine learning approaches

Among the most popular machine learning approaches: ANNs, SVMs, decision trees (i.e., RFs and gradient boosting (GB)), extreme learning machine ensemble (ELME), and regression linear statistical (MLR) were the most algorithms that integrated with GISs to predict and evaluate the potential of PV energy systems and solar radiation on rooftops. Accordingly, several integrated data-based models have been developed and explored as important tools for investigating the feasibility of installing PV panels on the rooftops of buildings, as well as for estimating the urban building characteristics and available solar energy on surfaces. Typically, the development of those predictive models involves four basic steps: data collection, data preprocessing, model training, and model testing. The data collection process includes gathering datasets related to the weather (e.g., sunshine period, outsider temperature, precipitation, and cloud coverage), space variables (e.g., latitude, longitude, and altitude), building characteristics (e.g., available rooftop area, shading factors), and total solar radiation on building rooftops, for the training and validation of the models. Data pre-processing involves data transformation, integration, and cleaning. The model training process always aims to train the model using the training dataset, whereas the model testing process involves the trained (i.e., developed) model's performance on a validation dataset using standard performance measures, such as the root mean square error, correction coefficient (R^2), mean absolute error, and variance coefficient to obtain an accurate, high-performance model.

Regarding the possibility of integrating PV energy systems into building structures, specifically on rooftops, SVM algorithms, including SVR and SVM, have been some of the most popular candidates for both short-and-long-term predictions, as summarized in Table 6. Assouline et al. [236] integrated an SVR algorithm (which is based on kernel functions for linear and nonlinear modeling) with a GIS to estimate the potential of PV energy generation on existing building rooftops at 1,895 communes in Switzerland. The factors related to space (latitude, altitude, and longitude), weather (temperature, sunshine period and cover of clouds), population, and building characteristics (e.g., the density of buildings, areas of the buildings, number of floors) were selected as input variables for the models. The results showed that integrating the SVR approach with a GIS is extremely useful for considering a wide range of significant input variables when estimating PV energy and for determining related additional characteristics with highly accurate results. This was followed by another research work by Assouline et al. [98], which concentrated on the evaluation of the physical, urban, technical, and societal potentials for rooftop PV electrical energy production at the commune level in Switzerland, by combining GIS techniques and an SVR algorithm. The authors calculated the available and appropriate rooftop areas for installing PV panels on buildings at each single commune level using ArcGIS, as shown in Fig. 3. The results demonstrated that 323 km^2 of building rooftops within an azimuth of $\pm 90^\circ$ (aligned in the southward direction) are appropriate rooftop areas for installing PV panels, which could produce 17.86 TWh of the corresponding annual PV electrical energy at the urban-area level in Switzerland. Mohajeri et al. [100] used an integrated SVM algorithm to classify the rooftop shapes of Geneva buildings, to evaluate the effects of rooftop characteristics on the rooftop area suitable for PV panel installations and on the received solar energy potential, as shown in Fig. 4. During the classification, a GIS technique (i.e., solar radiation analysis) was used in conjunction with Matlab to model the solar potential at two different scales- the level of a single building and the level of a city district- to verify a SITG-provided solar-city-scale model. The authors observed that the classification of solar-rooftop shape provides fundamental information for the design of new buildings, building rooftop interventions and facilitates improvements in rooftop-based solar energy generation efficiency. Regarding new building designs, building rooftop classification is based on the available and suitable areas for installing PV panels. The potential received solar energy encourages investors and policy-makers to select appropriate designs for rooftops that will enable the installation of more PV panels on rooftops and will provide greater electrical energy production at the lowest possible cost.

In addition to the aforementioned algorithms, other machine learning algorithms, such as the RF algorithm, played a significant role in the prediction of rooftop PV potential. Assouline [237] used SVR and RF algorithms integrated with a GIS to map the large-scale PV potential of buildings in Swaziland. The factors related to the building rooftop characteristics and horizontal solar radiation were considered as input variables for developing the predictive models. The author found that the RF algorithm-based models are useful for evaluating PVs on building rooftops. Likewise, Walch et al. [238] used the rooftop characteristics, horizontal solar irradiation, visibility of the sky, and shading factor as the essential input variables for studying annual rooftop solar irradiation, and developed five types of predictive models, based on the SVR, RF, MLR, KNN, and ELME algorithms. The results showed the superiority of the RF model, which had a high accuracy of 92%, over the other models. This was followed by another research work by Walch et al. [239], in which both the RF and ELME algorithms were used to evaluate the PV energy potential on 9.6 million building rooftops at a monthly-average-hourly temporal resolution; the authors also proposed a method for quantifying the uncertainty in the estimated potential, as shown in Fig. 5. Two types of "big data" were used: meteorology data (i.e., horizontal solar radiation, daily value of both surface reflections "albedo" and outside maximum temperature) and building data (i.e., rooftop areas, number of buildings, and related rooftop characteristics). The authors followed a hierarchical method, and estimated the physical (1), urban (2 and 3), and technical (4) potentials as evaluation criterion for the potential of PV energy production, as expressed in Eqs. (3)–(6). Their results showed that 55% of Swiss building rooftops are suitable areas for PV panel installations, with the potential to provide nearly 40% of Switzerland's current electrical energy consumption.

$$G_h(t) = G_B(t) + G_D(t) \tag{3}$$

$$G_t(t) = (1 - S_{sh}(t))^* G_{Bt}(t) + SVF^* G_{Dt}(t) + G_{Rt}(t) \tag{4}$$

Table 6
Results of solar photovoltaic energy potential estimates of rooftops at different urban scales using machine learning algorithms.

Type of building	Scale	Approach	Inputs	Key finding	Reference
Multiple	National	RF	Available rooftop area; rooftop shape; rooftop slope; rooftop direction; solar radiations on rooftops; factors of shadow	Rooftops in Switzerland can produce approximately 16.29 TWh/yr of electrical energy, equivalent to 25.3% of the total demand for 2017	Assouline et al. [84]
Multiple	1901 Communes/ municipalities	SVR	Sunshine period; temperature; precipitation, cloud cover; the tilted solar radiation on non-horizontal surface; latitude; altitude; longitude; population; density, type, and age of buildings, ground floor area of buildings; number of storeys; shading variables	328 km^2 of rooftops are suitable areas for installing (SPV) panels, and can provide 28% of electrical energy consumption for 2015	Assouline et al. [98]
Multiple	City	SVM	Number of each building rooftop areas; distribution of slopes; % of total rooftop area for each rooftop slope category; aspect distribution; % of total rooftop area for each rooftop aspect category	Classification of Solar PV rooftop-shape provides essential information for designing new buildings, and for incorporating SPV systems in building rooftops	Mohajeri et al. [100]
Multiple	National	MLR	Building characteristics: No. of buildings; size of rooftop area; rooftop orientation; solar; meteorological dataset	At US level, 8.13 billion square meters are suitable rooftop areas for installing SPV, which can provide 38.6% of total electrical energy consumption for 2013	Gagnon et al. [101]
Residential	City	MLR	Slope; elevation; area of rooftop; lot size (parcel area) on values of modeled photovoltaics	The rooftop SPV electrical energy potential is estimated to be approximately 190,000 MWh/yr	Carl [199]
Residential	City	MLR	Imagery: building age; No. of floors; HVAC type; available area of rooftops; height of floor; No. of buildings; etc	14.21 km^2 is the estimated rooftops, which can supply approximately 796 GWh/yr of electrical energy	Dehwah et al. [231]
Multiple	City	ANN	Horizontal diffused radiation; horizontal direct radiation; day of the year; hour of the day	An ANN exhibited high superiority in irradiation estimation on different rooftop orientations with $R^2 = 0.999$	Jurasz et al. [235]
Multiple	1895 communes/ municipalities	SVR	Temperature; sunshine; cloud cover; population; density, type, and area of building rooftops, number of storeys; latitude; altitude; longitude	SVR achieved monthly solar irradiance estimates with an error (RMSE) of 1.68 W/m^2	Assouline et al. [236]
Multiple	National	SVM, RF	Horizontal solar radiation on rooftop; available and appropriate PV rooftop areas; shading factors; rooftop characteristics	High potential for rooftop PV production, estimated at 61.3 TWH/yr of annual electrical energy demand	Assouline [237]
Multiple	3 cities	SVR, RF, MLR, KNN, ELME	Characteristics of building rooftops, such as roof aspect and roof tilt; Horizontal irradiation	RF provided annual solar irradiance estimates on rooftops with 92% accuracy	Walch et al. [238]
Multiple	9.6 million building rooftops	RF, ELME	Meteorological dataset: horizontal solar radiation; temperature; Building characteristics such as; type, age, area of buildings; No. of floors	55% of Swiss building rooftops are suitable areas for SPV installation with approximate production potential of 24 $\pm$ 9 TWh	Walch et al. [239]
Residential	Neighborhood	LR	Type of building; total area of rooftop; floor area; household density; average of household age; No. of adopters; expected period for payback; rooftop SPV potential	The possibility of the proposed method in estimating the amount and patterns of future diffusion in market for rooftop SPV systems	Lee and Hong [240]
Residential	National	MLR	No. of buildings; building type; available area for roofs; roof type; available solar radiation	The technical potential of German residential rooftops is approximately 148 TWh/a, with installation capacity of 208 GWp	Mainzer et al. [241]
Multiple	A city district	KN	Weather dataset such as temperature; urban data as such building characteristics; type of occupancy; energy systems; area topography	An integration of 50–100% of the available SPV potential is a preferred use of SPV electrical energy in buildings	Fonseca et al. [242]
Multiple	City	ML	Aerial images; geo-data of Buildings: rooftop slope; surface areas; irradiance file; temperature file	The ability of the proposed method to perform the spatiotemporal assessment for SPV potentials in urban random areas when only geographical building data are available	Mainzer et al. [243]
Residential	City districts	SVM, ANN	Data of imagery for building properties: rooftops; rooftop shape; shadows; solar radiance; panel cost	Thin film SPV panels outperformed other SPV panels	Joshi et al. [245]
Multiple	National	ANN, MLR	Weather variables: temperature; wind speed; humidity; irradiance; surface temperature; power	ANN models are superior to other MLR models in SPV energy prediction, with an error (RMSE) of 2.14, 6.16, and 5.54	Khandakar et al. [246]
Residential and industrial	A city district	ANN	Data of satellite imagery/LiDAR for available rooftop area; building typology; available annual irradiance	Wuhan rooftops have annual SPV electrical energy production potential of 17292.30 $\times 10^6$ kWh/yr	Huang et al. [247]
Multiple	National	ANN	Average of both temperature; humidity; sunshine period; wind speed; precipitation; longitude; latitude; latitude; and the month of year	Solar irradiance map provides basic information regarding the solar energy profile as input for implementing SPV energy systems	Rumbayan et al. [248]
Multiple	State	ANN	datasets of both meteorology and geography such as longitude, temperature; etc	High performance for ANN in solar energy prediction with accuracy (R value) of more than 95%	Anwar and Deshmukh [249]
Multiple	City	ANN	Weather variables including temperature; sunshine times; index of clearness; radiation; latitude; longitude	The correlation values were close to the global solar radiation measured on ground at different locations, whit an R value of 0.97	Yadav and Chandel [250]
Multiple	National	ANN		The developed model is a useful tool to predict the solar irradiance of Bangladesh, as well as	Rabbi et al. [251]

(continued on next page)

Table 6 (*continued*)

Type of building	Scale	Approach	Inputs	Key finding	Reference
			Climate data: temp; sunshine period; wind speed; precipitation; humidity; elevation; cloud coverage; atmospheric-pressure	providing sufficient information regarding the feasibility of solar energy projects	
Multiple	City	MLR	LiDAR data for building characteristics: height; length; width; footprint area; shape; solar radiation map	The research results can assist decision-makers in San Francisco to envisage building SPV potential and determine the appropriate positions to install SPV systems	Li et al. [252]
Multiple	City	SVM	Building area; rooftop characteristics; monthly solar irradiation on rooftop through LiDAR	Data-driven approach (SVM) is a useful tool for classifying the shape of Geneva building rooftops, as well as at the national level	Mohajeri et al. [253]
Multiple	National	SVM	Population; No. of buildings; total ground floor area of buildings; length of the street	R^2 between PV potential and related factors ranges between 85% and 95%	Mohajeri et al. [254]
Multiple	4 cities	RF, ELME	LiDAR dataset, including rooftop characteristics and vegetation; location of buildings	67% was the accuracy of results for rooftop-shape classification	Assouline et al. [255]
Multiple	City	GB	Solar irradiance; location; orientation of surfaces; cloud cover period	The ability of the GB approach to capture the nonlinear relationship between solar irradiance and prediction features for the studied periods	Vartholomaios [256]
Multiple	195 cities	ANN	Longitude; latitude; altitude; month of year; sunshine; amount cloud; temperature; relative humidity; intensity of solar radiation	A significant correlation between ANN predictions and the actual monthly average of solar radiation was estimated at more than 0.90	Fadare [257]
Multiple	15 cities	ANN, MLR, GA	Longitude; latitude; altitude; sunshine; amount cloud; temperature; relative humidity; wind speed	The proposed model can be helpful to the owner or building manager responsible for deciding whether or not to insert a SPV system and where to install it	Koo et al. [258]

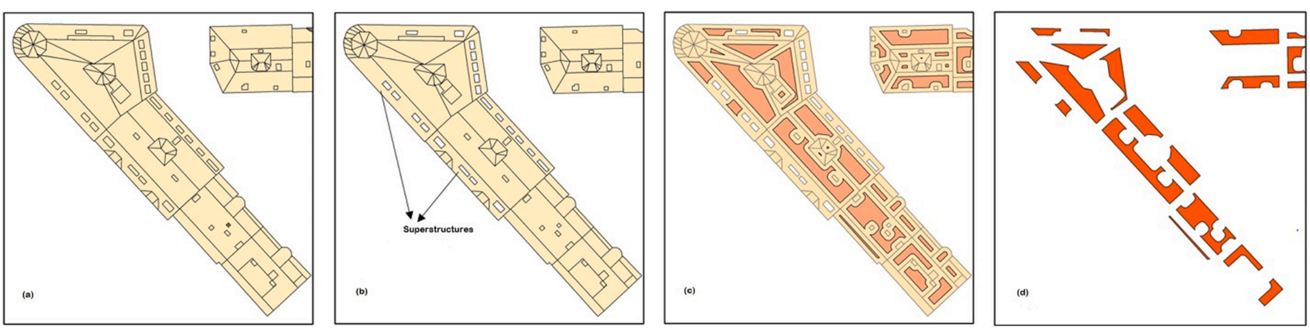

Fig. 3. Schematic view of estimation of appropriate rooftop areas on buildings via ArcGIS: (a) detailed rooftop polygon with all superstructures; (b) all rooftop superstructures removed; (c) a 100 cm^2 buffer around each single remaining rooftop area; (d) the final available and appropriate rooftop area for installing the PV panels after removal [98].

$$A_{pv} = A_t * C_{pv} * (1 - C_{sh}) \tag{5}$$

$$E_{pv} = G_t(t) * A_{pv} * \mu_{pv}(t) * Pf(t) \tag{6}$$

In the equations above, G_h is the solar radiation on the horizontal surface, G_B is the direct beam component, G_D is the diffuse component, G_t is the tilted radiation, S_{sh} is the hourly shading fraction, G_{Bt} is the direct tilted radiation component, SVF is the sky view factor, G_{Dt} is the diffuse tilted radiation component, G_{Rt} is the reflected tilted radiation component, A_{pv} is the available rooftop area for photovoltaic panel, A_t is the tilted rooftop area, C_{pv} is the paneled area coefficient, C_{sh} is the shaded area coefficient, μ_{pv} is the panel efficiency, and Pf is the performance factor.

Lee and Hong [240] combined agent-based modeling with a logistic regression algorithm and GIS to develop a hybrid predictive model for simulating the market spread of adopted PV panels on building rooftops in Nonhyeon, Seoul, South Korea, considering physical, socio-economic and demographic, social, economic, and technical factors. Three basic rules of behavior were determined based on panel logistic regression for rooftop PV adoption. Hybrid models for the different motivators were found to be better suited for representing the combined decision making process. Mainzer et al. [241] also combined the statistical method with a GIS to evaluate the residential rooftop-based PV technical potential for Germany at the municipal scale. The GIS technique was used to identify the annual mean of solar irradiation on the horizontal surfaces of each municipality. They concluded that the calculated technical potential was the most sensitive to assumptions regarding the efficiency of modules and usable roof areas. Fonseca et al. [242] evaluated and optimized the potential for both solar and PV panel production for building rooftops in Switzerland by integrating a GIS with the K-means clustering algorithm. The K-means algorithm was used to group areas with similar values for PV energy panels, and to assess the potential cost and solar energy use for each group in the city districts. The GIS served as a platform for collecting the overall results and displaying an understandable 4D visualization. Gagnon et al. [101] combined an MLR approach with a GIS to estimate rooftop characteristics and their quantities in all areas not covered by LiDAR data at the level of US cities. Subsequently, they modeled PV energy production for all rooftops to investigate the technical potential. The results showed 8.13 billion m^2 of appropriate rooftop areas, available to provide approximately 1118 GW of PV capacity and to satisfy approximately 1432 TWh of the annual electrical energy demand.

However, the integration of ANN algorithms with GISs to estimate PV electrical energy potential, considering the rooftop shape, available rooftop area, and shading impacts, did not give further attention compared to the other machine learning algorithms. Some previous studies utilized the integrated ANN algorithms with GIS data (i.e., the available geodata) to determine the types of rooftops, i.e., to evaluate

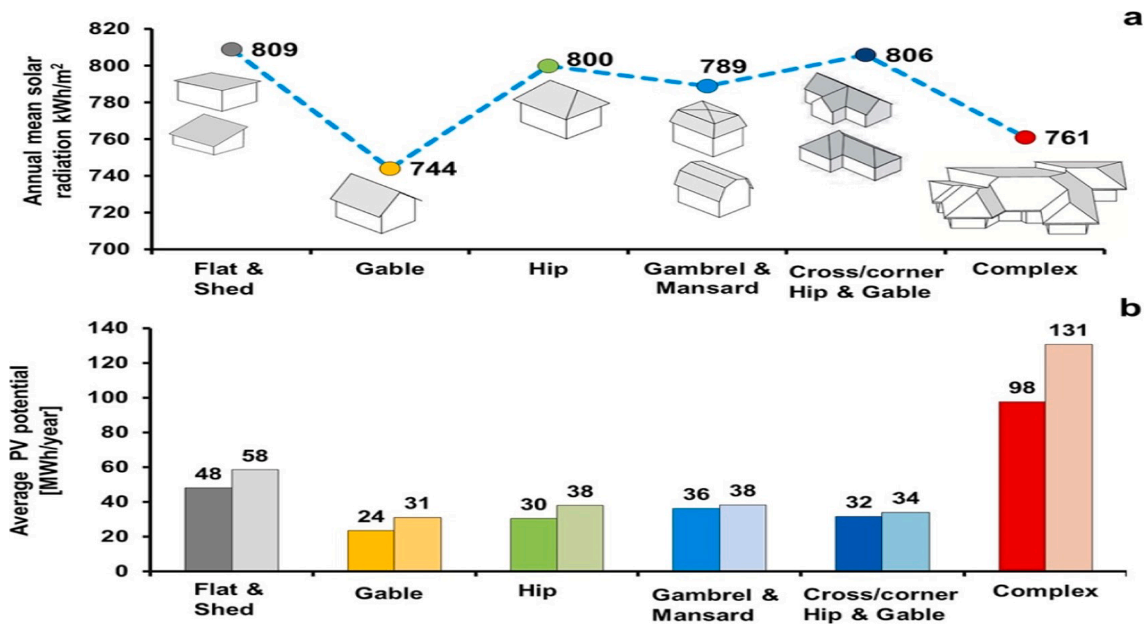

Fig. 4. Rooftop shape classification: (a) annual average of received solar radiation (kWh/m^2); and (b) average PV energy according to rooftop shape (MWh/year) [100].

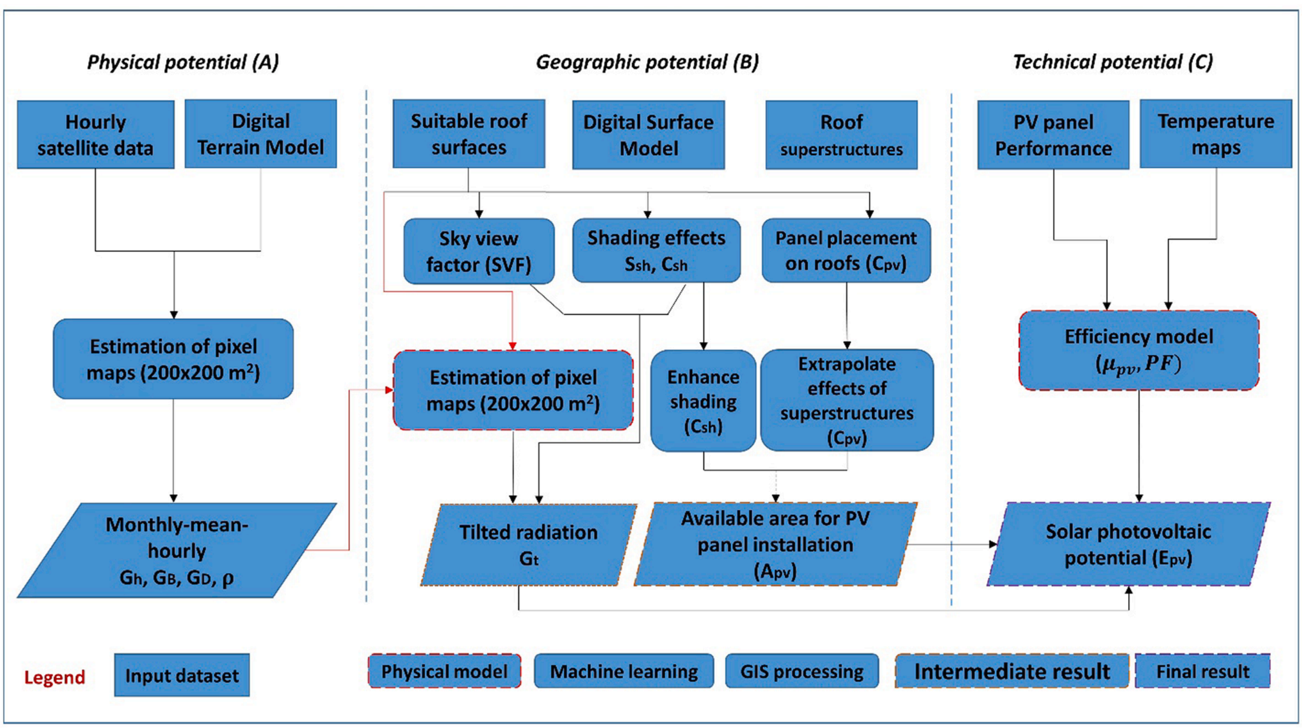

Fig. 5. Hierarchical methodology for estimating solar PV potential on rooftops of buildings [239].

the PV potential over building rooftops. In this context, Mainzer et al. [243] presented a new classification method to detect, assess, and categorize building rooftops as "photovoltaic" or "no photovoltaic". This method uses a backpropagation CNN and the geodata of Freiburg city to predict of each building rooftop if already equipped with the PV panels. Based on the prediction results, if the area of a rooftop unavailable for PV panel installation exceeded 90%, the rooftop area was considered as an occupied surface, and its potential was subtracted from the total potential. Bradbury et al. [244] used a CNN algorithm with geodata for four cities in California to predict the distribution of the locations of PV panels and to estimate their installation capacity, as well as to analyze the socio-economic correlates of PV panel deployment. Likewise, Joshi et al. [245] presented a two-stage classification approach for determining suitable rooftop areas for PV panel installations and evaluated three types of PV panel technologies in terms of electrical energy production and economic feasible for residential buildings in Abu Dhabi, EAU. In the first stage, satellite images and various image features were combined with an ANN to distinguish rooftop areas from non-rooftop areas and to calculate class probabilities for each type of rooftop area. In the second stage, the class probabilities from the first stage were utilized for features, in conjunction with shadowing factors. These features were used as a training dataset in an SVM algorithm to conduct the classification again. The results showed the superiority of the SVM, and indicated that the thin-film panels had a clear advantage over the other two types of PV technology. Khandakar et al. [246] compared the performance of an ANN with that of an MLR algorithm with regard to studying the effects of related environment factors (e.g., PV surface temperature, relative humidity, temperature) on the performance of PV panels in terms of output energy. They found that the predictive models of three ANNs with all features selected utilizing correlation feature selection (CFS) and relief feature selection exhibited high performance, with RMSE of 2.14, 6.16, and 5.54. Huang et al. [247] used a deep neural network (DNN) with satellite maps to determine the PV potential on the rooftops of buildings in Wuhan, China. They found that the urban building rooftops had the potential for generating 17292.30 * 10^6 kWh/year of electrical energy.

Despite the relatively modest contributions of machine learning algorithms (specifically the ANN and MLR) to investigating the potential of rooftop PV energy systems, however, these algorithms have had significant contributions to the estimation of solar radiation at different scales, including cities and national levels. For example, Rumbayan et al. [248] integrated an ANN with a GIS to map the solar energy potential in 30 cities of Indonesia and concluded that a solar map can provide important information regarding a solar energy source profile, i.e., as an input for the deployment of PV energy technologies. Anwar and Deshmukh [249] combined an ANN and GIS to evaluate and map solar energy source potential in 28 different locations of south India, using data from a long term period of approximately 22 years. Yadav and Chandel [250] used an ANN to evaluate the solar energy potential of the western Himalayan (in India); ArcGIS was utilized to map the monthly global solar radiation of the state of Himachal Pradesh. Rabbi et al. [251] developed a predictive model based on an integrated ANN to predict the monthly potentials of solar energy source in six cities in Bangladesh and found that the developed model could help predict solar irradiation and provide useful information regarding the feasibility of solar energy projects in Bangladesh. Uncertainties in the outputs/results of the machine learning models have been addressed through various methods. For example, the bootstrap method used by [98] and [237] to estimate the error intervals of the predicted values for input variables, including variables related to weather, solar radiation, buildings, and urban characteristics. Another method called the two-stage method [259] included the bootstrap-aggregating method, which was used by [238] and [239] to distinguish between model uncertainty (i.e., the uncertainty arising from the modeling process) and the data uncertainty (i.e., the uncertainty arising from input data), where the model uncertainty is estimated as the standard deviation of predictions. Other methods included the calculation-based method (for available rooftop, combined with solar radiation and energy conversion efficiency and compared with installed PV capacities) [241,243] and the stochastic method [258]. This was employed to address uncertainties related to the spatiotemporal variation of the horizontal solar radiation, the effects of both urban (i.e., trees and buildings) and rooftop characteristics (e.g., rooftop shape and suitable rooftop area), and other geographical parameters on the solar PV potential estimates via machine learning.

5. Discussion

The aforementioned GIS-based estimation approaches have been efficiently applied to assess the potential of rooftop PV energy systems at different scales of urban areas, including countries. Each approach has its own advantages, which can be useful in particular cases, resulting in highly accurate estimates of PV energy production on building rooftops in large-scale urban areas, including countries. On this basis, geostatistical approaches have been successfully integrated with GIS techniques to perform spatial data analyses, especially forecasting and mapping. The kriging methods were the most common and classical geostatistical approaches, and have been efficiently utilized for solar radiation mapping in urban buildings. Sampling approaches are used to compute variables of interest for a sample of known sites (where accurate and sufficient data are available), and the findings are extrapolated to the remaining parts of the studied area/target area. Modeling approaches, including 3D GIS approach, have also been employed to calculate variables of interest for an entire studied area by utilizing high-resolution aerial imagery, LiDAR, and other related data. Predictive models have been developed based on machine learning approaches to predict the PV energy production potential and received solar radiation of building rooftops at various urban scales. However, each approach has own disadvantages that may hinder its application when estimating the PV energy production potential in large-scale urban building rooftops, as summarized in Tables 7 and 8. Moreover, if an inappropriate approach is used, the expected estimation results may be unreliable and less accurate than those results obtained using an appropriate approach.

Geostatistical approaches for estimating the PV energy production of rooftops usually focus on the total solar energy received. Therefore, these approaches can provide accurate probabilistic outcomes with respect to diffuse radiation on tilted surfaces, the distribution map of solar radiation on the rooftop, and thus, the corresponding energy potentials. However, they require extensive calculations, especially for large-scale estimates. In addition, the geostatistical approach cannot be used successfully to estimate the characteristics of rooftops, including the estimation of the available rooftop areas, classification of building rooftops, and determinations of the effects of shading-factors and rooftop slopes. It is also difficult to include a large number of variables in a single operation of estimation or prediction of the rooftop PV potential. Hence, it is difficult to assess the solar energy potential in target areas when rooftop data are scarce. In this context, machine learning approaches can be an appropriate alternative to conduct spatial interpolations, particularly with the availability of measurement data at large scales.

As for sampling approaches, each approach has its own application, based on detailed information related to buildings, population, and other related factors. These approaches can provide highly accurate estimates for different rooftop characteristics for large-scale locations (e.g., available rooftop areas and suitable rooftop area for PV panel installations at different urban scales) when accurate data is available.

Table 7
Advantages and disadvantages of GIS-based rooftop solar PV potential estimation approaches.

Approach	Advantage	Disadvantage
Geostatistics-based	• Probabilistic outcomes • Explicit representation of the entire study area • Well-established theory	• Difficult to account for many features • Computation-intensive (heavy calculation) • Not very scalable
Sampling-based	• Based on real data and extrapolation • Scalable and very inexpensive • Probabilistic outcomes	• Does not guarantee satisfactory extrapolation • Diverse performance
Modeling-based	• Good accuracy • Specific details • Possibility of automated application in several areas	• Need more time • Computation-intensive (heavy calculation) • Difficult to scale up (small-to-large-scales) • Need experience
Machine learning-based	• High performance with accurate outcomes • Ability to consider/account for many input features • Adaptability and flexibility • Easily scalable (small-to-large-scales) • Both data and stellate imagery can be used	• Large amount of data is needed • Sometime difficult to train, for some models, such as ANN • Experience needed

Table 8
Applicability (Y) and inapplicability (N) of approaches for estimating significant features of rooftop solar photovoltaic potential.

Approach	Solar radiation mapping	Tilted radiation	Available area	Shading	Slope and aspect	Rooftop type
Geostatistics-based	Y	Y	N	N	N	N
Sampling-based	N	N	Y	Y	Y	Y
Modeling-based	Y	N	Y	Y	Y	Y
Machine learning-based	Y	Y	Y	Y	Y	Y

However, these approaches require thorough-statistical-validation with an appropriate extrapolation strategy for samples to provide precise results. Moreover, in the case of the solar radiation mapping for building rooftops, the diffuse radiation on tilted surfaces cannot be efficiently estimated. This affects the efficiency of these approaches, because without accurate estimates of the diffuse tilted radiation, rooftop solar radiation data cannot be generated. In particular, the amount of solar radiation on tilted rooftops is the sum of the direct, diffuse and reflected tilted components of radiation [170,260,261] and represents the rooftop solar radiation map of the buildings [265]. One of the possible solutions for overcoming the limitations of sampling approaches is to combine them with machine learning approaches. This may be a suitable alternative, i.e., computing the available rooftop area and then performing spatial interpolation for the target area, which could provide accurate results.

In the last few years, GIS-based modeling approaches, including the 3D GIS approach, have been prevalent due to the significant increase in the availability of LiDAR datasets around the world. In addition, modeling approaches enable automated computation and provide satisfactory results, specifically if the LiDAR datasets are available at very high-resolution. As a result, they have been considered as the best approaches for investigating and estimating the multiple parameters related to rooftop PV potential, including the appropriate rooftop area for PV panel installation, shading factor, rooftop slope, and rooftop solar radiation. However, GIS-based modeling approaches require substantial computation time to obtain precise and reliable results. In addition, low quality of LiDAR data may lead to unsatisfactory results. Therefore, GIS-based modeling approach, which are based on LiDAR data, are more appropriately for micro-to-medium scale studies, such as those at the scale of city districts, small cities. These approaches may be unreliable at large scales, such as national and regional scales (e.g., the EU). Thus, machine learning approaches represent suitable alternative approach for PV evaluation strategies at large urban scales, including national and regional scales. This is consistent with the findings of Assouline et al. [143]. By comparing modeling approaches with sampling and geostatistical approaches, it was found that the modeling approaches may be the best for rooftop PV energy estimates at different urban scales (i.e., small-to-medium scales). This is attributed to the availability of high-resolution LiDAR data, which leads to the possibility of obtaining accurate results.

Machine learning approaches, although not yet extensively explored, can be considered as the best alternative approach compared to LiDAR-based modeling approaches for assessing and estimating the potential for PV energy generation on rooftops. These approaches can provide rooftop solar radiation maps, classify building rooftops, calculate suitable rooftop areas for PV panel installation and corresponding investment costs, and forecast future PV capabilities. A machine learning approach does not require additional time to calculate all the related variables for determining the PV energy potential on building rooftops. Second, the machine learning approach requires representative data to learn from. Third, machine learning can be successfully applied at large scales, such as mega-cities and countries [262,263], with minimal effort. Fourth, machine learning approach is a rapidly growing field, and is conceptually equivalent to advanced sampling approaches. It is being used in countless domains to effectively utilize the massive amounts of data available. Therefore, machine learning-based developed models can be used to solve many problems related to determining rooftop PV energy generation potential. In particular, these approaches have become a core component of spatial analyses in GIS techniques. For instance, vector machine algorithms can be used to create rooftop classification layers. In addition, clustering algorithms, which enable large amounts of input point data to be processed, identify meaningful groups within such data and separate the data from scatter noise. Predictive algorithms, such as geographically weighted regression, allow us to model spatially uneven relationships [264].

Suggestively, the combination of a machine learning approach with another approach, such as a sampling or a geostatistical or modeling-based approach, may yield high-precision estimates for the rooftop PV energy generation potential in different large scale buildings. In addition to addressing many issues related to the complexity of urban topography and the lack of input data at large scales. In particular, hybrid approach usually takes the advantages of both basic approaches for more reliable and accurate estimates for rooftop PV systems. This is especially true when dealing with complex urban topology and muddled data across target areas. The weather conditions and characteristics of both population and building rooftops are important parameters for short-and-long term energy generation estimates in the context of large-scale built environments. This would promote the gradual deployment of solar photovoltaic panel technologies and mitigate fossil fuel-related power emissions across various urban scales, including countries, specifically when there are more in-depth investigation studies.

6. Conclusions

Decentralized energy systems from renewable photovoltaic resources, clean and available, are gradually replacing conventional energy systems in urban environments. Rooftop solar photovoltaic panels are, therefore, an attractive form of renewable electrical energy generation, especially with technological development and the permanent cost reduction of photovoltaic panels, as well as the availability of unexploited areas and the ease of installation on building structures. However, the optimal use of these systems requires accurate and reliable estimates of power supply (i.e., rooftop solar PV potential) and demand values of electrical energy, along with the design of an intelligent distribution system that can be integrated with power girds. Geographic information systems-based estimation is justified as a promising approach, especially it can be combined with LiDAR to build robust/powerful approaches to provide high-resolution estimates of rooftop solar PV potential. It also provides the possibility of investigating variables of interest, such as rooftop azimuth, slope, rooftop areas, footprint areas, and solar irradiance, as well as extracting the geometrical characteristics of buildings e.g., rooftops from orthophotagraphies. Accordingly, this study provides a comprehensive review for GISs-based rooftop solar photovoltaic potential estimation approaches that have been applied at different scales, including neighborhoods, cities, and countries. Simultaneously, this study classified GISs-based estimation approaches into sampling approaches, geostatistical approaches, modeling approaches, and machine learning approaches. The applications, advantages, and disadvantages of each approach were reviewed and discussed. Based on the above, the following conclusions were derived. With regard to solar radiation mapping, geostatistical approaches, especially kriging models, provide good probabilistic outputs, leading to the measurement of errors related to the estimates. However, these approaches require extensive calculations. Sampling approaches are most appropriate for computing different rooftop characteristics at large scales if high-resolution data are available. However, thorough statistical validation of the samples, with appropriate extrapolation strategies, is required to provide accurate and reliable results. Modeling approaches, including the 3D GIS approach, are good methodologies for quantifying the effects of multiple variables related to the potential estimates of solar PVs on rooftops, including the rooftop characteristics, as well as for estimating the rooftop solar radiation in small scale studies, such as neighborhoods or cities, especially with the availability of LiDAR datasets. However, they are troublesome for large scale studies, such as country-wide studies, because of the large amount of calculation required (heavy calculations) to obtain satisfying outcomes. However, these GIS-based approaches, especially machine learning approaches can be applied for temporally and spatially assessing future power systems with decentralized electrical energy grids, where the approach outputs can be utilized to suggest effective-policies for incorporating rooftop photovoltaics into built environments. Machine learning approaches are a promising alternative to the modeling approaches, which require heavy computations to calculate all input variables leading to the rooftop solar PV potential. Particularly, machine learning is a rapidly growing field that is used in countless areas to take advantage of the vast amount of data available. In conclusion, this study considers that the development of a new methodology integrating GISs with machine learning to provide an accurate and less computationally -demanding-alternative to LiDAR-based approaches, will contribute significantly to large-scale estimates of rooftop solar photovoltaic potentials and related uncertainties. This would provide accurate and reliable estimates of the actual electrical energy output from the photovoltaic panels to be installed on building rooftops at large scales, including countries, promoting the widespread deployment of clean, low-carbon energy systems in built environments.

Declaration of Competing Interest

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

Acknowledgment

This work was supported by the research fund of Hanyang University (HY-2020).

References

[1] Alaloul WS, Liew MS, Zawawi NAWA, Kennedy IB. Industrial revolution 4.0 in the construction industry: challenges and opportunities for stakeholders. Ain Shams Eng J 2020;11:225–30. https://doi.org/10.1016/j.asej.2019.08.010.
[2] UN United Nations, Department of Economic and Social Affairs 2018. Available online at https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html.
[3] UN United Nations, Department of Economic and Social Affairs. World population prospects 2019. https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/files/documents/2020/Jan/wpp2019_highlights.pdf.
[4] Architecture 2030. New buildings: operational emissions 2020. Available online at https://architecture2030.org/new-buildings-operations/.
[5] Alhamwi A, Medjroubi W, Vogt T, Agert C. Development of a GIS-based platform for the allocation and optimisation of distributed storage in urban energy systems. Appl Energy 2019;251:113360. https://doi.org/10.1016/j.apenergy.2019.113360.
[6] Jalil-Vega F, Kerdan IG, Hawkes AD. Spatially-resolved urban energy systems models to study Decarbonisation pathways for energy services in cities. Appl Energy 2020;262:114445. https://doi.org/10.1016/j.apenergy.2019.114445.
[7] Li G, Xuan Q, Akram MW, Akhlaghi YG, Liu H. Building integrated solar concentrating systems: a review. Appl Energy 2020;260:114288. https://doi.org/10.1016/j.apenergy.2019.114288.
[8] IEA. Global solar PV market set for spectacular growth over next 5 years, October 21, 2019. Accessed on August 1, 2020. https://www.iea.org/news/global-solar-pv-market-set-for-spectacular-growth-over-next-5-years.
[9] Parida B, Iniyan S, Goic R. A review of solar photovoltaic technologies. Renew Sustain Energy Rev 2011;15:1625–36. https://doi.org/10.1016/j.rser.2010.11.032.
[10] Shukla AK, Sudhakar K, Baredar P. Recent advancement in BIPV product technologies: a review. Energy Build 2017;140:188–95. https://doi.org/10.1016/j.enbuild.2017.02.015.
[11] Debbarma M, Sudhakar K, Baredar P. Thermal modeling, exergy analysis, performance of BIPV and BIPVT: a review. Renew Sustain Energy Rev 2017;73:1276–88. https://doi.org/10.1016/j.rser.2017.02.035.
[12] Chen F, Yin H. Fabrication and laboratory-based performance testing of a building-integrated photovoltaic-thermal roofing panel. Appl Energy 2016;177:271–84. https://doi.org/10.1016/j.apenergy.2016.05.112.
[13] Sun L, Lu L, Yang H. Optimum design of shading-type building-integrated photovoltaic claddings with different surface azimuth angles. Appl Energy 2012;90:233–40. https://doi.org/10.1016/j.apenergy.2011.01.062.
[14] Tiwari GN, Mishra RK, Solanki SC. Photovoltaic modules and their applications: a review on thermal modelling. Appl Energy 2011;88:2287–304. https://doi.org/10.1016/j.apenergy.2011.01.005.
[15] Chow T-T. A review on photovoltaic/thermal hybrid solar technology. Appl Energy 2010;87:365–79. https://doi.org/10.1016/j.apenergy.2009.06.037.
[16] Held M, IIg R. Update of environmental indicators and energy payback time of CdTe PV systems in Europe. Progress in Photovoltaics Res. Appl. 2011;19:614–26. https://doi.org/10.1002/pip.1068.
[17] Commission, EN. Paris agreement 2016. Available online at https://ec.europa.eu/clima/policies/international/negotiations/paris_en.
[18] Thopil GA, Sachse CE, Lalk J, Thopil MS. Techno-economic performance comparison of crystalline and thin film PV panels under varying meteorological conditions: a high solar resource southern hemisphere case. Appl Energy 2020;275:115041. https://doi.org/10.1016/j.apenergy.2020.115041.
[19] Alhamwi A, Medjroubi W, Vogt T, Agert C. GIS-based urban energy systems models and tools: introducing a model for the optimisation of flexibilisation technologies in urban areas. Appl Energy 2017;191:1–9. https://doi.org/10.1016/j.apenergy.2017.01.048.
[20] Jonas A, Kristina O, Georgios M, Florian R, Viktor D, Ralph E. A review of modeling approaches and tools for the simulation of district-scale energy systems. Renew Sustain Energy Rev 2015;52:1391–404. https://doi.org/10.1016/j.rser.2015.07.123.
[21] Manfren M, Caputo P, Costa G. Paradigm shift in urban energy systems through distributed generation: methods and models. Appl Energy 2011;88:1032–48. https://doi.org/10.1016/j.apenergy.2010.10.018.
[22] Buonomano A, Calise F, Palombo A, Vicidomini M. BIPVT systems for residential applications: an energy economic analysis for European Climates. Appl Energy 2016;184:1411–31. https://doi.org/10.1016/j.apenergy.2016.02.145.
[23] Agrawal B, Tiwari GN. Optimizing the energy and exergy of building integrated photovoltaic thermal (BIPVT) systems under cold climatic conditions. Appl Energy 2010;87:417–26. https://doi.org/10.1016/j.apenergy.2009.06.011.
[24] Allegrini J, Orehounig K, Mavronmatidis G, Ruesch F, Dorer V, Evins R. A review of modeling approaches and tools for the simulation of district-scale energy systems. Renew Sustain Energy Rev 2015;52:1391–404. https://doi.org/10.1016/j.rser.2015.07.123.
[25] Shukla AK, Sudhakar K, Baredar P. Exergetic assessment of BIPV module using parametric and photonic energy methods: a review. Energy Build 2016;119:62–73. https://doi.org/10.1016/j.enbuild.2016.03.022.
[26] Ghani F, Duke M, Carson JK. Estimation of photovoltaic conservation efficiency of a building integrated photovoltaic/thermal (BIPV/T) collector array using an artificial neural network. Sol Energy 2012;86:3378–87. https://doi.org/10.1016/j.solener.2012.09.001.
[27] Angelis-Dimakis A, Biberacher M, Dominquez J, Fiorese G, Gadocha S, Gnansounou E, et al. Methods and tool to evaluate the availability of renewable energy sources. Renew Sustain Energy Rev 2011;15:1182–200. https://doi.org/10.1016/j.rser.2010.09.049.
[28] Camargo LR, Zink R, Dorner W, Stoeglehner G. Spatio-temporal modeling of roof-top photovoltaic panels for improved technical potential assessment and electricity peak load offsetting at the municipal scale. Comput, Environ Unbar Syst 2015;52:58–69. https://doi.org/10.1016/j.compenvurbsys.2015.03.002.
[29] Calvert K, Pearce JM, Mabee WE. Toward renewable energy geo-information infrastructures: applications of GIScience and remote sensing that build institutional capacity. Renew Sustain Energy Rev 2013;18:416–29. https://doi.org/10.1016/j.rser.2012.10.024.
[30] Roche S. Geographic information science I: why does a smart city need to be spatially enabled? Prog Hum Geogr 2014;38(5):703–11. https://doi.org/10.1177/0309132513517365.
[31] Sisternes FJ-de, Jenkins JD, Botterud A. The value of energy storage in decarbonizing the electricity sector. Appl Energy 2016;175:368–79. https://doi.org/10.1016/j.apenergy.2016.05.014.
[32] Kanters J, Wall M, Kjellsson E. The solar map as a knowledge base for solar energy use. Energy Procedia 2014;48:1597–606. https://doi.org/10.1016/j.egypro.2014.02.180.
[33] Schallenberg-Rodriguez J. Photovoltaic techno-economical potential on roofs in regions and islands: the case of the Canary Islands. Methodological review and methodology proposal. Renew Sustain Energy Rev 2013;20:219–39. https://doi.org/10.1016/j.rser.2012.11.078.
[34] Byrne J, Taminiau J, Kurdgelashvili L, Kim KN. A review of the solar city concept and methods to assess rooftop solar electric potential, with an illustrative application to the city of Seoul. Renew Sustain Energy Rev 2015;41:830–44. https://doi.org/10.1016/j.rser.2014.08.023.

[35] Freitas S, Catita C, Redweik P, Brito MC. Modeling solar potential in the urban environment: state-of-the-are review. Renew Sustain Energy Rev 2015;41: 915–31. https://doi.org/10.1016/j.rser.2014.08.060.

[36] Zhang X, Lovati M, Vigna I, Widen J, Han M, Gal C. A review of urban energy systems at building cluster level incorporating renewable-energy-source (RES) envelope solutions. Appl Energy 2018;230:1034–56. https://doi.org/10.1016/j.apenergy.2018.09.041.

[37] Peng C, Huang Y, Wu Z. Building-integrated photovoltaics (BIPV) in architectural design in china. Energy Build 2011;43:3592–8. https://doi.org/10.1016/j.enbuild.2011.09.032.

[38] Gaur A, Tiwari GN. Performance of photovoltaic modules of different solar cells. J Solar Energy 2013;2013:1–13. https://doi.org/10.1155/2013/734581.

[39] Rajoria CS, Gupta PK, Agrawal S, Tiwari GN, Singh D. effect of different photovoltaic materials on energetic and Exergetic performance of photovoltaic thermal arrays. MATEC Web Conf 2017;95:1–4. https://doi.org/10.1051/matecconf/20179501006.

[40] Bruton TM. General trends about photovoltaics based on crystalline silicon. Sol Energy Mater Sol Cells 2002;72:3–10. https://doi.org/10.1016/S0927-0248(01)00145-3.

[41] Vats K, Tiwari GN. Energy and exergy analysis of a building integrated semitransparent photovoltaic thermal (BISPVT) system. Appl Energy 2012;96: 409–16. https://doi.org/10.1016/j.apenergy.2012.02.079.

[42] Satos IP-D, Ruther R. The potential of building-integrated (BIPV) and building-applied photovoltaics (BAPV) in single-family, urban residences at low latitudes in Brazil. Energy Build 2012;50:290–7. https://doi.org/10.1016/j.enbuild.2012.03.052.

[43] Rajoria CS, Agrawal S, Chabhash S, Tiwari GN, Chauhan DS. A novel investigation of building integrated photovoltaic thermal (BiPVT) system: a comparative study. Sol Energy 2016;131:107–18. https://doi.org/10.1016/j.solener.2016.02.037.

[44] Brinkworth BJ, Cross BM, Marshall RH, Yang H. Thermal regulation of photovoltaic cladding. Sol Energy 1997;61(3):169–78. https://doi.org/10.1016/S0038-092X(97)00044-3.

[45] Debbarma M, Sudhakar K, Baredar P. Comparison of BIPV and BIPVT: a review. Resour-Efficient Technol 2017;3:263–71. https://doi.org/10.1016/j.reffit.2016.11.013.

[46] Shukla A, Sudhakar K, Baredar P. A comprehensive review on design of building integrated photovoltaic system. Energy Build 2016;128:99–110. https://doi.org/10.1016/j.enbuild.2016.06.077.

[47] Zimmerman R, Panda A, Bulovic V. Techno-economic assessment and deployment strategies for vertically-mounted photovoltaic panels. Appl Energy 2020;276:115149. https://doi.org/10.1016/j.apenergy.2020.115149.

[48] Sarmah N, Richards BS, Makllick TK. Design development and indoor performance analysis of a low concentrating dielectric photovoltaic module. Sol Energy 2014;103:390–401. https://doi.org/10.1016/j.solener.2014.02.029.

[49] Sellami N, Mallick TK. Optical characterization and optimisation of a static window integrated concentrating photovoltaic system. Sol Energy 2013;91: 273–82. https://doi.org/10.1016/j.solener.2013.02.012.

[50] Sabry M, Abdel-Hadi YA, Ghitas A. PV-integrated CPC for transparent facades. Energy Build 2013;66:480–4. https://doi.org/10.1016/j.enbuild.2013.07.059.

[51] Zhu L, Shao Z, Sun Y, Soebarto V, Gao F, Zillante G. Indoor daylight distribution in a room with integrated dynamic solar concentrating façade. Energy Build 2018;158:1–13. https://doi.org/10.1016/j.enbuild.2017.10.008.

[52] Quesada G, Rousse D, Dutil Y, Badache M, Halle S. A comprehensive review of solar facades. Opaque solar facades. Renew Sustain Energy Rev 2012;16: 2820–32. https://doi.org/10.1016/j.rser.2012.01.078.

[53] Bergamasco L, Asinari P. Scalable methodology for the photovoltaic solar energy potential assessment based on available roof surface area: application to piedmont region (Italy). Sol Energy 2011;85:1041–55. https://doi.org/10.1016/j.solener.2011.02.022.

[54] Izquierdo S, Montanes C, Dopazo C, Fueyo N. Roof-top solar energy potential under performance-based building energy codes: the case of Spain. Sol Energy 2011;85:208–13. https://doi.org/10.1016/j.solener.2010.11.003.

[55] Jacques DA, Gooding J, Giesekam J-J, Tomlin AS, Crook R. Methodology for the assessment of PV capacity over a city region using low-resolution LiDAR data and application to the city of Leeds (UK). Appl Energy 2014;124:28–34. https://doi.org/10.1016/j.apenergy.2014.02.076.

[56] Kabir Md-H, Endlicher W, Jagermeyr J. Calculation of bright roof-tops for solar PV applications in Dhaka megacity. Bangladesh. Renewable Energy 2000;35: 1760–4. https://doi.org/10.1016/j.renene.2009.11.016.

[57] Peng J, Lu L. Investigation on the development potential of rooftop PV system in Hong Kong and its environmental benefits. Renew Sustain Energy Rev 2013;27: 149–62. https://doi.org/10.1016/j.rser.2013.06.030.

[58] Yang H, Zheng G, Lou C, An D, Burnett J. Grid-connected building-integrated photovoltaics: a Hong Kong case study. Sol Energy 2004;76:55–9. https://doi.org/10.1016/j.solener.2003.09.007.

[59] Defaix PR, van Sark WGJHM, Worrell E, E-de Visser. Technical potential for photovoltaics on buildings in the EU-27. Sol Energy 2012;86:2644–53. https://doi.org/10.1016/j.solener.2012.06.007.

[60] Martinopoulos G. Are rooftop photovoltaic systems a sustainable solution for Europe? A life cycle impact assessment and cost analysis. Appl Energy 2020;257: 114035. https://doi.org/10.1016/j.apenergy.2019.114035.

[61] Barkaszi S F, Dunlop J P. Discussion of strategies for mounting photovoltaic arrays on rooftops. In: International Solar Energy Conference, Washington, DC, USA, April 21-25; 2001. p. 333–8. Doi: 10.1115/SED2001-142.

[62] Anctil A, Lee E, Lunt RR. Net energy and cost benefit of transparent organic solar cells in building-integrated applications. Appl Energy 2020;261:114429. https://doi.org/10.1016/j.apenergy.2019.114429.

[63] Sadineni SB, Atallah F, Boehm RF. Impact of roof integrated PV orientation on the residential electricity peak demand. Appl Energy 2012;92:204–10. https://doi.org/10.1016/j.apenergy.2011.10.026.

[64] Schoen TJN. Building-integrated PV installations in the Netherlands: examples and operational experiences. Sol Energy 2001;70(6):467–77. https://doi.org/10.1016/S0038-092X(00)00142-0.

[65] Biyik E, Araz M, Hepbasli A, Shahrestani M, Yao R, Shao L, et al. A key review of building integrated photovoltaic (BIPV) systems. Eng Sci Technol Int J 2017;20: 833–58. https://doi.org/10.1016/j.jestch.2017.01.009.

[66] Baljit S-SS, Chan H-YS, Sopian K. Review of building integrated applications of photovoltaic and solar thermal systems. J Cleaner Prod ;137:677–89. https://doi.org/10.1016/j.jclepro.2016.07.150.

[67] Lu W, Peng Y, Xue F, Chen K, Niu Y, Chen X. The fusion of GIS and building information modeling for big data analytics in managing development sites. Comprehensive Geogr Inform Sci 2018:345–59. https://doi.org/10.1016/B978-0-12-409548-9.09677-9.

[68] Longley PA. Geographic information science and systems. International Encyclopedia of Human Geography, 2nd ed.; 2020. p. 29–36. Doi: 10.1016/B978-0-08-102295-5.10557-8.

[69] Johnston K, Ver Hoef JM, Krivoruchko K, Lucas N. Using ArcGIS Geostatistical Analyst, GIS by ESRI. https://dusk.geo.orst.edu/gis/geostat_analyst.pdf.

[70] Javed N, Saqib E, Razag A, Saeed U. 3.16- Revamping urban immovable property tax system by using GIS and MIS: a case study of reforming urban taxation systems using tools and technology. Comprehensive Geogr Inf Sci 2018:272–96. https://doi.org/10.1016/B978-0-12-409548-9.09691-3.

[71] Chakraborty A, McMillan A. 2.17- GIS and scenario analysis: tools for better urban planning. Comprehensive Geogr Inf Sci 2018:371–80. https://doi.org/10.1016/B978-0-12-409548-9.09649-4.

[72] Maliene V, Grigonis V, Palevicuis V, Griffiths S. Geographic information system: old principles with new capabilities. Urban Des International 2011;16:1–6. https://doi.org/10.1057/udi.2010.25.

[73] Luca C. Generative platform for urban and regional design. Autom Constr 2007; 16:70–7. https://doi.org/10.1016/j.autcon.2005.10.008.

[74] Sola A, Corchero C, Salom J, Sanmarti M. Simulation tools to build urban-scale energy models: a review. Energies 2018;11:1–24. https://doi.org/10.3390/en11123269.

[75] Sumathi VR, Natesan U, Sarkar C. GIS-based approach for optimized siting of municipal solid waste landfill. Waste Manage 2008;28:2146–60. https://doi.org/10.1016/j.wasman.2007.09.032.

[76] Wang H, Chen D, Duan H, Yin F, Niu Y. Characterizing urban building metabolism with a 4D-GIS model: a case study in china. J Cleaner Prod 2019;228: 1446–54. https://doi.org/10.1016/j.jclepro.2019.04.341.

[77] Machete R, Falcao AP, Gomes MG, Rodrigues AM. The use of 3D GIS to analyse the influence of urban context on buildings' solar energy potential. Energy Build 2018;177:290–302. https://doi.org/10.1016/j.enbuild.2018.07.064.

[78] Rossetto R, Filippis GD, Borsi I, Forglia L, Massimiliano C, Criollo R, et al. Environ Model Software 2018;107:210–30. https://doi.org/10.1016/j.envsoft.2018.06.007.

[79] Sui DZ. GIS-based urban modeling: practices, problems, and prospects. Int J Geogr inform Sci 1998;12(7):651–71. https://doi.org/10.1080/136588198241581.

[80] ArcGIS CityEngine, Esri. Accessed on August 17, 2020. https://www.esri.com/en-us/arcgis/products/arcgis-cityengine/overview.

[81] QGIS Desktop. Accessed on August 17, 2020. https://www.osgeo.org/projects/qgis/.

[82] QGIS, Open Source Geographic Information System. Accessed on August 17, 2020. https://www.qgis.org/en/site/.

[83] Mastrucci A, Baume O, Stazi F, Leopold U. Estimating energy savings for the residential building stock of an entire city: A GIS-based statistical downscaling approach applied to Rotterdam. Energy Build 2014;75:358–67. https://doi.org/10.1016/j.enbuild.2014.02.032.

[84] Assouline D, Mohajeri N, Scartezzini J-L. Large-scale rooftop solar photovoltaic potential estimation using Random forests. Appl Energy 2018;217:189–211. https://doi.org/10.1016/j.apenergy.2018.02.118.

[85] Nouvel R, Mastrucci A, Leopold U, Baume O, Coors V, Eicker U. Combining GIS-based statistical and engineering urban heat consumption models: towards a new framework for multi-scale policy support. Energy Build 2015;107:204–12. https://doi.org/10.1016/j.enbuild.2015.08.021.

[86] Ma J, Cheng JCP. Estimation of the building energy use intensity in the urban scale by integrating GIS and big data technology. Appl Energy 2016;183:182–92. https://doi.org/10.1016/j.apenergy.2016.08.079.

[87] ML, Machine Learning in ArcGIS, Esri. Accessed on August 18, 2020. https://www.esri.com/about/newsroom/arcuser/machine-learning-in-arcgis/.

[88] Quan SJ, Li Q, Augenbroe G, Brown J, Yang PP-J. A GIS-based energy balance modeling system for urban solar buildings. Energy Procedia 2015;75:2946–52. https://doi.org/10.1016/j.egypro.2015.07.598.

[89] Nageler P, Zahrer G, Heimrath R, Mach T, Mauthner F, Leusbrock I, et al. Novel validated method for GIS based automated dynamic urban building energy simulations. Energy 2017;139(15):142–54. https://doi.org/10.1016/j.energy.2017.07.151.

[90] Ascione F, Masi RFD, F-de Rossi, Fistola R, Sasso M, Vanoli GP. Analysis and diagnosis of the energy performance of buildings and districts: methodology,

validation and development of urban energy maps. Cities 2013;35:270–383. https://doi.org/10.1016/j.cities.2013.04.012.
[91] Chen Y, Hong T, Luo X, Hooper B. Development of city buildings dataset for urban building energy modeling. Energy Build 2019;183:252–65. https://doi.org/10.1016/j.enbuild.2018.11.008.
[92] Mastrucci A, Baume O, Stazi F, Salvucci S, Leopold U. A GIS-based approach to estimate energy savings and indoor thermal comfort for urban housing stock retrofitting. BauSIM 2014;9:190–7. http://www.ibpsa.org/proceedings/bausimPapers/2014/p1136_final.pdf.
[93] Chen Y, Hong T. Impacts of building geometry modeling methods on the simulation results of urban building energy models. Appl Energy 2018;215:717–35. https://doi.org/10.1016/j.apenergy.2018.02.073.
[94] ArcGIS API for Python, Deep learning models in ArcGIS, esri. Learn [accessed on August 18, 2020]. https://www.esri.com/arcgis-blog/products/api-python/analytics/deep-learning-models-in-arcgis-learn/.
[95] ArcGIS Pro, An overview of the deep learning toolset [accessed on August 18, 2020]. https://pro.arcgis.com/en/pro-app/tool-reference/image-analyst/an-overview-of-the-deep-learning-toolset-in-image-analyst.htm.
[96] ArcGIS, arcgis.learn module [accessed on August 18, 2020]. https://developers.arcgis.com/python/api-reference/arcgis.learn.html.
[97] ArcGIS Pro, esri. Deep learning in ArcGIS Pro [accessed on August 19, 2020]. https://pro.arcgis.com/en/pro-app/help/analysis/image-analyst/deep-learning-in-arcgis-pro.htm.
[98] Assouline D, Mohajeri N, Scartezzini J-L. Quantifying rooftop photovoltaic solar energy potential: a machine learning approach. Sol Energy 2017;141(1):278–96. https://doi.org/10.1016/j.solener.2016.11.045.
[99] Re Cecconi F, Moretti N, Tagliabue LC. Application of artificial neural network and geographic information system to evaluate retrofit potential in public school buildings. Renew Sustain Energy Rev 2019;110:266–77. https://doi.org/10.1016/j.rser.2019.04.073.
[100] Mohajeri N, Assouline D, Guiboud B, Bill A, Gudmundsson A, Scartezzini J-L. A city-scale roof shape classification using machine learning for solar energy applications. Renewable Energy 2018;121:81–93. https://doi.org/10.1016/j.renene.2017.12.096.
[101] Gagnon P, Margolis R, Melius J, Phillips C, Elmore R. Estimating rooftop solar technical potential across the US using combination of GIS-based methods, lidar data, and statistical modeling. Environ Res Lett 2018;13:024027. https://doi.org/10.1088/1748-9326/aaa554.
[102] Mrowczynska M, Skiba M, Bazan-Krzywoszanska A, Sztubecka M. Household standards and socio-economic aspects as a factor determining energy consumption in the city. Appl Energy 2020;264:114680. https://doi.org/10.1016/j.apenergy.2020.114680.
[103] Marzouk M, Othman A. Planning utility infrastructure requirements for smart cities using the integration between BIM and GIS. Sustain Cities Soc 2020;57:102120. https://doi.org/10.1016/j.scs.2020.102120.
[104] Ali U, Shamsi MH, Hoare C, ODonnell J. GIS-based residential building energy modeling at district scale. In: Proceedings of Building Simulation Optimization Conference, Cambridge, UK: 11-12 September 2018. https://pdfs.semanticscholar.org/0c91/6d2bc5c31e8bed544a027f695161e86b95fe.pdf.
[105] Ding C, Zhou N. Using residential and office building archetypes for energy efficiency building solutions in an urban scale: a China case study. Energies 2020;13:3210. https://doi.org/10.3390/en13123210.
[106] Buffat R, Froemelt A, Heeren N, Raubal M, Hellweg S. Big data GIS analysis for novel approaches in building stock modeling. Appl Energy 2017;208:277–90. https://doi.org/10.1016/j.apenergy.2017.10.041.
[107] Ahn Y, Sohn D-W. The effect of neighbourhood-level urban form on residential building energy use: A GIS-based model using building energy benchmarking data in Seattle. Energy Build 2019;96:124–33. https://doi.org/10.1016/j.enbuild.2019.05.018.
[108] Quan SJ, Li Q, Augenbroe G, Brown J, Yang PP-J. Urban data and building energy modeling: a GIS-based urban building energy modeling system using the Urban-EPC Engine. Planning Support Systems and Smart Cities. Springer; 2015. p. 447–69. Doi: 10.1007/978-3-319-18368-8_24.
[109] Fabbri K, Zuppiroli M, Ambrogio K. Heritage buildings and energy performance: mapping with GIS tools. Energy Build 2012;48:137–45. https://doi.org/10.1016/j.enbuild.2012.01.018.
[110] Lilis GN, Giannakis G, Katsigarakis K, Rovas D. District-aware building energy performance simulation model generation from GIS and BIM data. In: Proceedings of building simulation optimization conference, Cambridge, UK; 2018. p. 177–84. https://discovery.ucl.ac.uk/id/eprint/10056593.
[111] Alhamwi A, Medjroubi W, Vogt T, Agert C. Modelling urban energy requirements using open source data and models. Appl Energy 2018;231:1100–8. https://doi.org/10.1016/j.apenergy.2018.09.164.
[112] Ranalli J, Alhamwi A. Configurations of renewable power generation in cities using open source approaches: with Philadelphia case study. Appl Energy 2020;269:115027. https://doi.org/10.1016/j.apenergy.2020.115027.
[113] Amado M, Poggi F, Amado A-R, Breu S. A cellular approach to Net-Zero Energy Cities. Energies 2017;10(11):1–17. https://doi.org/10.3390/en10111826.
[114] Chen Y, Hong T, Piette MA. Automatic generation and estimation of urban building energy models based on city datasets for city-scale building retrofit analysis. Appl Energy 2017;205:323–35. https://doi.org/10.1016/j.apenergy.2017.07.128.
[115] Pemmen P, Lauster M, Mans M, Osterhage T, Muller D. CityGML import and export for dynamic building performance simulation in Modelica. In: Building simulation and optimization conference (BSO16); 2016. http://www.ibpsa.org/proceedings/BSO2016/p1047.pdf.
[116] Kolbe TH, Groger G, Plumer L. CityGML: Interoperable access to 3D city Models. Geo-information for Disaster Management. Berlin, Heidelberg: Springer; 2005. p. 883–99. https://doi.org/10.1007/3-540-27468-5_63.
[117] Reinhart CF, Dogan T, Jakubiec JA, Rakha T, Sang A. UMI-an urban simulation energy environment for building energy use, daylighting and walkability. In: Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28; 2013. https://www.aivc.org/sites/default/files/p_1404.pdf.
[118] Nouvel R, Brassel NK-H, Bruse ME, Duminil E, Coors V, Eicker U, et al. SIMSTADT, a new workflow-driven urban energy simulation platform for CityGML city models. In: Proceedings of international conference CISBAT 2015 buildings and districts sustainability from nano to urban scale. No. EPFL-CONF-21347. LESO-PB, EPFL. https://core.ac.uk/download/pdf/148017431.pdf.
[119] Mutani G, Todeschi V. Building modeling at neighborhood scale. Energ Effi 2020;13:1353–86. https://doi.org/10.1007/s12053-020-09882-4.
[120] Choi Y, Suh J, Kim S-M. GIS-based solar radiation mapping, site evaluation, and potential assessment: a review. Appl Sci 2019;9:1960. https://doi.org/10.3390/app9091960.
[121] Resch B, Sagl G, Törnros T, Bachmaier A, Eggers J-B, Herkel S, et al. GIS-based planning and modeling for renewable energy: challenges and future research avenues. ISPRS Int J Geo-Inf 2014;3:662–92. https://doi.org/10.3390/ijgi3020662.
[122] Martin AM, Dominguez J, Amador J. Applying LIDAR datasets and GIS based model to evaluate solar potential over roofs: a review. Energy 2015;3(3):326–43. https://doi.org/10.3934/energy.2015.3.326.
[123] Bazilian M, Onyeji I, Liebreich M, MacGill I, Chase J, Shah J, et al. Re-considering the economics of photovoltaic power. Renew Energy 2013;53:329–38. https://doi.org/10.1016/j.renene.2012.11.029.
[124] Branker K, Pathak MJM, Pearce JM. A review of solar photovoltaic levelized cost of electricity. Renew Sustain Energy Rev 2011;15:4470–82. https://doi.org/10.1016/j.rser.2011.07.104.
[125] Lang T, Gloerfeld E, Girod B. Don't just follow the sun- a global assessment of economic performance for residential building photovoltaics. Renew Sustain Energy Rev 2015;42:932–1651. https://doi.org/10.1016/j.rser.2014.10.077.
[126] Izquierdo S, Rodrigues M, Fueyo N. A method for estimating the geographical distribution of the available roof surface area for large-scale photovoltaic energy-potential evaluations. Sol Energy 2008;82:929–39. https://doi.org/10.1016/j.solener.2008.03.007.
[127] Groppi D, Santoli L-d, Cumo F, Garcia A. A GIS-based model to assess buildings energy consumption and usable solar energy potential in urban areas. Sustain Cities Soc 2018;40:546–58. https://doi.org/10.1016/j.scs.2018.05.005.
[128] Horan W, Byrne S, Shawe R, Moles R, O'Regan B. A geospatial assessment of the rooftop Decarbonisation potential of industrial and commercial zoned buildings: an example of Irish cities and regions. Sustain Energy Technol Assess 2020;38:100651. https://doi.org/10.1016/j.seta.2020.100651.
[129] Khan J, Arsalan MH. Estimation of rooftop solar photovoltaic potential using geo-spatial techniques: a perspective from planned neighborhood of Karachi-Pakistan. Renew Energy 2016;90:188–203. https://doi.org/10.1016/j.renene.2015.12.058.
[130] Bocca A, Bottaccioli L, Chiavazzo E, Fasano M, Macii A, Asinari P. Estimating photovoltaic energy potential from a minimal set of randomly sampled data. Renew Energy 2016;97:457–67. https://doi.org/10.1016/j.renene.2016.06.001.
[131] Nguyen H-T, Pearce JM. Automated quantification of solar photovoltaic potential in cities. Int Rev Spatial Plan Sustain Develop 2013;1(1):49–60. https://doi.org/10.14246/irspsd.1.1_49.
[132] Wiginton LK, Nguyen HT, Pearce JM. Quantifying rooftop solar photovoltaic potential for regional renewable energy policy. Computer, Environ Urban Syst 2010;34:345–57. https://doi.org/10.1016/j.compenvurbsys.2010.01.001.
[133] Mallinis G, Karteris M, Theodoridou I, Tsioukas V, Karteris M. Development of a nationwide approach for large scale estimation of green roof retrofitting areas and roof-top solar energy potential using VHR natural colour orthoimagery and DSM data over Thessaloniki, Greece. Remote Sensing Lett 2014;5(6):548–57. https://doi.org/10.1080/2150704X.2014.933276.
[134] Vardimon R. Assessment of the potential for distributed photovoltaic electricity production in Israel. Renew Energy 2011;36:591–4. https://doi.org/10.1016/j.renene.2010.07.030.
[135] Karteris M, Slini T, Papadopoulos AM. Urban solar energy potential in Greece: a statistical calculation model of suitable built roof areas for photovoltaics. Energy Build 2013;62:459–68. https://doi.org/10.1016/j.enbuild.2013.03.033.
[136] Nguyen HT, Pearce JM, Harrap R, Barber G. The application of LiDAR to assessment of rooftop solar photovoltaic deployment potential in a municipal district unit. Sensors 2012;12:4534–58. https://doi.org/10.3390/s120404534.
[137] Liu G, Wu W, Ge Q, Dai E, Wan Z, Zhou Y. A GIS method for assessing roof-mounted solar energy potential: a case study in Jiangsu, China. Environ Eng Manage J 2011;10(6):843–8. http://www.eemj.icpm.tuiasi.ro/pdfs/vol10/no6/21_262_Liu_11.pdf.
[138] Guangxu L, Wenxiang W, Quansheng G, Erfu D, Zhiwei W, Yang Z. GIS-based assessment of roof-mounted solar energy potential in Jiangsu, China. In: 2011 Second international conference on digital manufacturing & automation. IEEE; 2011. doi:10.1109/ICDMA.2011.142.
[139] Ordonez J, Jadraque E, Alegre J, Martinez G. Analysis of the photovoltaic solar energy capacity of residential rooftops in Andalusia (Spain). Renew Sustain Energy Rev 2010;14:2122–30. https://doi.org/10.1016/j.rser.2010.01.001.
[140] Yuan J, Farnham C, Emura K, Lu S. A method to estimate the potential of rooftop photovoltaic power generation for a region. Urban Clim 2016;17:1–19. https://doi.org/10.1016/j.uclim.2016.03.001.

[141] Thai C, Brouwer J. Challenges estimating distributed solar potential with utilization factors: California universities case study. Appl Energy 2021;282: 116209. https://doi.org/10.1016/j.apenergy.2020.116209.
[142] Maliva RG. Geostatistical methods and applications. In: Aquifer characterization techniques. Springer hydrogeology. Cham: Springer; 2016. p. 595–617. https://doi.org/10.1007/978-3-319-32137-0_20.
[143] Assouline D, Mohajeri N, Scartezzini J-L. Estimation of large-scale solar rooftop PV potential for smart grid integration: a methodological review. Sustain Interdependent Networks, Springer 2018;145:173–219. https://doi.org/10.1007/978-3-319-74412-4_11.
[144] Webster R, Oliver MA. Local estimation or prediction: Kriging, Geostatistics for environmental scientists, 2nd ed. Statistics for Social Sciences. Wiley; 2007. p. 1–315. https://www.wiley.com/en-kr/Geostatistics+for+Environmental+Scientists%2C+2nd+Edition-p-9780470028582.
[145] Kanevski M, Timonin V, Pozdnukhov A. Machine learning for spatial environmental data, theory, applications, and software. EPFL Press; 2009. Doi: 10.1201/9781439808085.
[146] Geostatistics, Kriging in geostatistical analyst. Rater Interpolation toolset concepts, ArcGIS Desktop, esri. Available online at: https://pro.arcgis.com/en/pro-app/tool-reference/3d-analyst/how-kriging-works.htm.
[147] Hong T, Koo C, Park K, Park H. A GIS (geographic information system)-based optimization model for estimation the electricity generation of the rooftop PV (photovoltaic) system. Energy 2014;65:190–9. https://doi.org/10.1016/j.energy.2013.11.082.
[148] D'Agostino V, Zelenka A. supplementing solar radiation network data by co-kriging with satellite images. Int J Climatol 1992;12:749–61. https://doi.org/10.1002/joc.3370120707.
[149] Alsamamra H, Ruiz-Arias J-A, Pozo-Vazquez D, Tovar-Pescador J. A comparative study of ordinary and residual kriging techniques from mapping global solar radiation over southern Spain. Agric For Meteorol 2009;149:1343–57. https://doi.org/10.1016/j.agrformet.2009.03.005.
[150] Moreno A, Gilabert MA, Martinez B. Mapping daily global solar irradiation over Spain: a comparative study of selected approaches. Sol Energy 2011;85:2072–84. https://doi.org/10.1016/j.solener.2011.05.017.
[151] Fathizad H, Mobin MH, Gholamnia A, Sodaiezadeh H. Modeling and mapping of solar radiation using geostatistical analysis methods in Iran. Arabian J Geosci 2017;10(391):1–13. https://doi.org/10.1007/s12517-017-3130-x.
[152] Bertrand C, Housmans C, Leloux J, Journee M. Solar irradiation from the energy production of residential PV systems. Renew Energy 2018;125:306–18. https://doi.org/10.1016/j.renene.2018.02.036.
[153] Koo C, Hong T, Jeong K, Ban C, Oh J. Development of the smart photovoltaic system blind and its impact on net-zero energy solar buildings using technical-economic-political analysis. Energy 2017;124:382–96. https://doi.org/10.1016/j.energy.2017.02.088.
[154] McKenney DW, Pelland S, Poissant Y, Morris R, Hutchinson M, Papadopol P, et al. Spatial insolation models for photovoltaic energy in Canada. Sol Energy 2008;82: 1049–61. https://doi.org/10.1016/j.solener.2008.04.008.
[155] Wang LZ, Tan HW, Ji L, Wang D. A method for evaluating photovoltaic potential in China based on GIS platform. In: Proceedings of earth and environmental science 2017;93: 012056. doi:10.1088/1755-1315/93/1/012056.
[156] Rehman S, Ghori SG. Spatial estimation of global solar radiation using geostatistics. Renew Energy 2000;21:583–605. https://doi.org/10.1016/S0960-1481(00)00078-1.
[157] Lee M, Koo C, Hong T, Park HS. Framework for the mapping of the monthly average daily solar radiation using an advanced case-based reasoning and a geostatistical technique. Environ Sci Technol 2014;48(8):4604–12. https://doi.org/10.1021/es405293u.
[158] Mishra T, Rabha A, Kumar U, Arunachalam K, Sridhar V. Assessment of solar power potential in a hill state of India using remote sensing and geographic information system. Remote Sens Appl: Soc Environ 2020;19:100370. https://doi.org/10.1016/j.rsase.2020.100370.
[159] Wong MS, Zhu R, Liu Z, Lu L, Peng J, Tang Z, et al. Estimation of Hong Kong's solar energy potential using GIS and remote sensing technologies. Renew Energy 2016;99:325–35. https://doi.org/10.1016/j.renene.2016.07.003.
[160] Geostatistical Analyst, ArcMAP, ArcGIS. Classification trees of the interpolation methods offered in Geostatistical Analyst. Available online at: https://desktop.arcgis.com/en/arcmap/latest/extensions/geostatistical-analyst/classification-trees-of-the-interpolation-methods-offered-in-geostatistical-analyst.htm.
[161] Aydin NY, Kentel E, Duzgun HS. GIS-based site selection methodology for hybrid renewable energy systems: a case study from western Turkey. Energy Convers Manage 2013;70:90–106. https://doi.org/10.1016/j.enconman.2013.02.004.
[162] Amjad F, Shah LA. Identification and assessment of sites for solar farms development using GIS and density based clustering technique- a case of Pakistan. Renew Energy 2020;155:761–9. https://doi.org/10.1016/j.renene.2020.03.083.
[163] Zhang Y, Ren J, Pu Y, Wang P. Solar energy potential assessment: a framework to integrate geographic, technological, and economic indices for a potential analysis. Renew Energy 2020;149:577–86. https://doi.org/10.1016/j.renene.2019.12.071.
[164] Carrion JA, Estrella E, Aznar Dols F, Ramos Ridao A. The electricity production capacity of photovoltaic power plants and the selection of solar energy sites in Andalusia (Spain). Renew Energy 2008;33:545–52. https://doi.org/10.1016/j.renene.2007.05.041.
[165] Quiros E, Pozo M, Ceballos J. Solar potential of rooftops in Caceres city, Spain. J Maps 2018;14(1):44–51. https://doi.org/10.1080/17445647.2018.1456487.
[166] Sun Y-W, Hof A, Wang R, Liu J, Lin Y-J, Yang D-W. GIS-based approach for potential analysis of solar PV generation at the regional scale: a case study of Fujian Province. Energy Policy 2013;58:248–59. https://doi.org/10.1016/j.enpol.2013.03.002.
[167] Gomez-Exposito A, Arcos-Vargas A, Gutierrez-Garcia F. On the potential contribution of rooftop PV to a sustainable electricity mix: the case of Spain. Renew Sustain Energy Rev 2020;132:110074. https://doi.org/10.1016/j.rser.2020.110074.
[168] Porse E, Fournier E, Cheng D, Hirashiki C, Gustafson H. Net solar generation potential from urban rooftops in Los Angeles. Energy Policy 2020;145:111461. https://doi.org/10.1016/j.enpol.2020.111461.
[169] Lopez-Ruiz H, Blazquez J, Vittorio M. Assessing residential solar rooftop potential in Saudi Arabia using nighttime satellite images: a study for the city of Riyadh. Energy Policy 2020;140:111399. https://doi.org/10.1016/j.enpol.2020.111399.
[170] Melius J, Margolis R, Ong S. Estimating rooftop suitability for PV: a review of methods, patents, and validation techniques. National Renewable Energy Laboratory, United States: N. p., 2013: p. 1–30. doi:10.2172/1117057.
[171] Suomalainen K, Wang V, Sharp B. Rooftop solar based on LiDAR data: bottom-up assessment at neighbourhood level. Renew Energy 2017;111:463–75. https://doi.org/10.1016/j.renene.2017.04.025.
[172] Hofierka J, Kanuk J. Assessment of photovoltaic in urban areas using open-source solar radiation tools. Renew Energy 2009;34:2206–14. https://doi.org/10.1016/j.renene.2009.02.021.
[173] Suri M, Hofierka J. A new GIS-based solar radiation model and its application to photovoltaic assessments. Trans GIS 2004;8(2):175–90. https://doi.org/10.1111/j.1467-9671.2004.00174.x.
[174] Jo JH, Otanicar TP. A hierarchical methodology for the mesoscale assessment of building integrated roof solar energy systems. Renew Energy 2011;36: 2992–3000. https://doi.org/10.1016/j.renene.2011.03.038.
[175] Nguyen HT, Pearce JM. Incorporating shading losses in solar photovoltaic potential assessment at the municipal scale. Sol Energy 2012;86:1245–60. https://doi.org/10.1016/j.solener.2012.01.017.
[176] Nguyen HT, Pearce JM. Automated quantification of solar photovoltaic potential in cities. Int Rev Spatial Plan Sustainable Develop 2013;1:49–60. https://doi.org/10.14246/irspsd.1.1_49.
[177] Brito MC, Gomes N, Santos T, Tenedorio JA. Photovoltaic potential in a Lisbon suburb using Lidar data. Sol Energy 2012;86:283–8. https://doi.org/10.1016/j.solener.2011.09.031.
[178] Strzalka A, Alam N, Duminil E, Coors V, Eicker. Large scale integration of photovoltaics in cities. Appl Energy 2012;93:413–21. doi:10.1016/j.apenergy.2011.12.033.
[179] Boz MB, Calvert K, Brownson JRS. An automated model for rooftop PV systems assessment in ArcGIS using LiDAR. Energy 2015;3(3):401–20. https://doi.org/10.3934/energy.2015.3.401.
[180] Gooding J, Crook R, Tomlin AS. Modelling of roof geometrics from low-resolution LiDAR data for city-scale solar energy applications using a neighboring buildings method. Appl Energy 2015;148:93–104. https://doi.org/10.1016/j.apenergy.2015.03.013.
[181] Huang Y, Yu B, Hu Z, Wu J, Wu B. Locating suitable roofs for utilization of solar energy in downtown area using airborne LiDAR data and object-based method: a case study of the Lujiazui region, Shanghai. In: 2012 Second international workshop on earth observation and remote sensing application. IEEE. DOI: 10.1109/EORSA.2012.6261192.
[182] Latif ZA, Zaki NAM, Salleh SA. GIS-based estimation of rooftop solar photovoltaic potential using lidar. In: 2012 IEEE 8th international colloquium on signal processing and its applications. doi: 10.1109/CSPA.2012.6194755.
[183] Lukac N, Zlaus D, Seme S, Zalik B, Stumberger G. Rating of roofs' surfaces regarding their solar potential and suitability for PV systems, based on LiDAR data. Appl Energy 2013;102:803–12. https://doi.org/10.1016/j.apenergy.2012.08.042.
[184] Sreckovic N, Lukac N, Zalik B, Stumberger G. Determining roof surface for the installation of PV (photovoltaic) systems, based on LiDAR (Light Detection And Ranging) data, pyranometer measurements, and distribution network configuration. Energy 2016;96:404–14. https://doi.org/10.1016/j.energy.2015.12.078.
[185] Bill A, Mohajeri N, Scartezzini J-L. 3D model for solar energy potential on buildings from urban lidar data. Eurographics Workshop on Urban Data Modeling and Visualization; 2016. p. 51–6. Doi: 10.2312/udmv.20161420.
[186] Choi Y, Rayl J, Tammineedi C, Brownson JRS. PV analyst: coupling ArcGIS with TRNSYS to assess distributed photovoltaic in urban areas. Sol Energy 2011;85: 2924–39. https://doi.org/10.1016/j.solener.2011.08.034.
[187] Verso A, Martin A, Amador J, Dominguez J. GIS-based method to evaluate the photovoltaic potential in the urban environments: the particular case of Miraflores de la Sierra. Sol Energy 2015;117:236–45. https://doi.org/10.1016/j.solener.2015.04.018.
[188] Mavromatidis G, Orehounig K, Carmeliet J. Evaluation of photovoltaic integration potential in a village. Sol Energy 2015;121:152–68. https://doi.org/10.1016/j.solener.2015.03.044.
[189] Tooke TR, Coops NC, Voogt JA, Meitner MJ. Tree structure influences on rooftop-received solar radiation. Landscape Urban Plann 2011;102:73–81. https://doi.org/10.1016/j.landurbplan.2011.03.011.
[190] Agugiaro G, Remondino F, Stevanato G, Filippi R-D, Furlanello C. Estimation of solar radiation on building roofs in mountainous areas. In: Int. Arch, Photogramm. Remote Sens. Spatial Inf. Sci., XXVlll-3/W22; 2011. p. 155–60. Doi: 10.5194/isprsarchives-XXXVIII-3-W22-155-2011.
[191] Agugiaro G, Nex F, Remondino F, Filippi R-D, Droghetti S, Furlandello C. Solar radiation estimation on building roofs and web-based solar cadaster. ISPRS Ann

Photogramm Remote Sens Spatial Inf Sci 2012;I-2:177–82. https://doi.org/10.5194/isprsannals-I-2-177-2012.
[192] Catita C, Redweik P, Pereira J, Brito MC. Extending solar potential analysis in buildings to vertical facades. Comput Geosci 2014;66:1–12. https://doi.org/10.1016/j.cageo.2014.01.002.
[193] Kodysh JB, Omitaomu OA, Bhaduri BL, Neish BS. Methodology for estimating solar potential on multiple building rooftops for photovoltaic systems. Sustain Cities Soc 2013;8:31–41. https://doi.org/10.1016/j.scs.2013.01.002.
[194] Liang J, Gong J, Li W, Ibrahim AN. A visualization-oriented 3D method for efficient computation of urban solar radiation based on 3D–2D surface mapping. Int J Geogr Inform 2014;28(4):780–98. https://doi.org/10.1080/13658816.2014.880168.
[195] Palmer D, Koumpli E, Cole I, Gottschalg R, Betts T. A GIS-based method for identification of wide area rooftop suitability for minimum size PV systems using LiDAR data and photogrammetry. Energies 2018;11(12):3506. https://doi.org/10.3390/en11123506.
[196] Suri M, Huld TA, Dunlop ED. PV-GIS: a web-based solar radiation database for the calculation of PV potential in Europe. Int J Sustain Energ 2005;24(2):55–67. https://doi.org/10.1080/14786450512331329556.
[197] Kassner R, Koppe W, Schuttenberg T, Bareth G. Analysis of the solar potential of roofs by using official LiDAR data. In:Proceedings of the international society for photogrammetry, remote sensing and spatial information sciences (ISPRS Congress); 2008. p. 399–404. http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=14BFA1D362D697DBB7D5BEC49BCF34A0?doi=10.1.1.159.185&rep=rep1&type=pdf.
[198] Saretta E, Caputo P, Frontini F. An integrated 3D GIS-based method for estimating the urban potential of BIPV retrofit of facades. Sustain Cities Soc 2020;62:102410. https://doi.org/10.1016/j.scs.2020.102410.
[199] Carl C. Calculating solar photovoltaic potential on residential rooftops in Kailua Kona, Hawaii, Thesis; 2014. https://www.semanticscholar.org/paper/Calculating-solar-photovoltaic-potential-on-in-Carl/aae97892560ef427157294ccf3fc5fa5317b134d.
[200] Rodriguez L-R, Duminil E, Ramos JS, Eicker U. Assessment of the photovoltaic potential at urban level based on 3D city models: a case study and new methodological approach. Sol Energy 2017;146:264–75. https://doi.org/10.1016/j.solener.2017.02.043.
[201] Guen ML, Mosca L, Perera ATD, Coccolo S, Mohajeri N. Scartezzini J-L. Improving the energy sustainability of a Swiss village through building renovation and renewable energy integration. Energy Build 2018;158:906–923. Doi: 10.1016/j.enbuild.2017.10.057.
[202] Lukac N, Seme S, Zlaus D, Stumberger G, Zalik B. Buildings roofs photovoltaic potential assessment based on lidar (light detection and ranging) data. Energy 2014;66:598–609. https://doi.org/10.1016/j.energy.2013.12.066.
[203] Jo JH, Rose Z, Cross J, Daebel E, Verderber A, Kostelnick JC. Application of airborne LiDAR data and geographic information systems (GIS) to develop a distributed generation system for the town of Normal, IL. AIMS Energy 2015;3(2):173–83. https://doi.org/10.3934/energy.2015.2.173.
[204] Chow A, Li S, Fung AS. Modeling urban solar energy with high spatiotemporal resolution: a case study in Toronto, Canada. Int J Green Energy 2016;13(11):1090–101. https://doi.org/10.1080/15435075.2016.1170686.
[205] Mainzer K, Schlund D, Killinger S, McKenna R, Fichtner W. Rooftop PV potential estimations: automated orthographic satellite image recognition on publicly available data. In: 32nd European photovoltaic solar energy conference and exhibition, fraunhofer; 2016. p. 2930–3. DOI: 10.4229/EUPVSEC20162016-7EO.2.3.
[206] Santos T, Gomes N, Freire S, Brito MC, Santos L, Tenedorio JA. Applications of solar mapping in the urban environment. Appl Geogr 2014;51:48–57. https://doi.org/10.1016/j.apgeog.2014.03.008.
[207] Saadaoui H, Ghennioui A, Ikken B, Rhinane H, Maanan M. Using GIS and photogrammetry for assessing solar photovoltaic potential on flat roofs in urban area case of the city of Ben Guerir/Morocco. Int Arch Photogramm Remote Sens Spatial Inf Sci 2019;XLII-4/W12:155–66. Doi: 10.5194/isprs-archives-XLII-4-W12-155-2019.
[208] Song J, Choi Y. Evaluation of rooftop photovoltaic electricity generation systems for establishing a green campus. Geosyst Eng 2015;18(1):51–60. https://doi.org/10.1080/12269328.2014.997892.
[209] Jochem A, Hofle B, Rutzinger M, Pfeifer N. Automatic roof plane detection and analysis in airborne lidar point clouds for solar potential assessment. Sensors 2009;9:5241–62. https://doi.org/10.3390/s90705241.
[210] Buffat R, Grassi S, Raubal M. A scalable method for estimating rooftop solar irradiation potential over large regions. Appl Energy 2018;216:389–401. https://doi.org/10.1016/j.apenergy.2018.02.008.
[211] Margolis R, Gagnon P, Melius J, Phillips C, Elmore R. Using GIS-based methods and Lidar to estimate rooftop solar technical potential in US cities. Environ Res Lett 2017;12:074013. https://doi.org/10.1088/1748-9326/aa7225.
[212] Kucuksari S, Khaleghi AM, Hamidi M, Zhang Y, Szidarovszky F, Bayraksan C, et al. An integrated GIS, optimization and simulation framework for optimal PV size and location in campus area environments. Appl Energy 2014;113:1601–13. https://doi.org/10.1016/j.apenergy.2013.09.002.
[213] Li Y, Ding D, Liu C, Wang C. A pixel-based approach to estimation of solar energy potential on building roofs. Energy Build 2016;129:563–73. https://doi.org/10.1016/j.enbuild.2016.08.025.
[214] Biljecki F, Huevelink GBM, Ledoux H, Stoter J. Propagation of potential error in 3D GIS: estimation of the solar irradiation of building roofs. Int J Geogr Inform Sci 2015;29(12):2269–94. https://doi.org/10.1080/13658816.2015.1073292.
[215] Zhang Z, Lv Y, Tian J, Pan Y. An integrative approach for solar energy potential estimation through 3D modeling of buildings and Trees. Can J Remote Sensing 2015;41:126–34. https://doi.org/10.1080/07038992.2015.1043004.
[216] Sanchez-Aparicio M, Martin-Jimenez J, Del Pozo S, Gonzalez-Gonzalez E, Laguela S. Ener3DMap-Solarweb roofs: a geographical web-based platform to compute photovoltaic potential. Renew Sustain Energy Rev 2021;135:110203. https://doi.org/10.1016/j.rser.2020.110203.
[217] Thebault M, Clivillé V, Berrah L, Desthieux G. Multicriteria roof sorting for the integration of photovoltaic systems in urban environments. Sustain Cities Soc 2020;60:102259. https://doi.org/10.1016/j.scs.2020.102259.
[218] Hafeez S. 3D rooftop photovoltaic potential calculation using GIS techniques; a case study of F-11 sector Islamabad, Photovoltaic system and GIS. In: 2014 12th international conference on frontiers of information technology. IEEE; 2014. p. 187–92. DOI: 10.1109/FIT.2014.43.
[219] Ko L, Wang J-C, Chen C-Y, Tsai H-Y. Evaluation of the development potential of rooftop solar photovoltaic in Taiwan. Renew Energy 2015;76:582–95. https://doi.org/10.1016/j.renene.2014.11.077.
[220] Aboushal EA. Applying GIS technology for optimum selection of photovoltaic panels "spatially at defined urban area in Alexandria, Egypt. Alexandria Eng J 2018;57:4167–76. https://doi.org/10.1016/j.aej.2018.11.005.
[221] Gupta Y, Sharma M. Estimating sustainable location for harvesting solar power using geographical information systems and remote sensing methods. J Inform Optimization Sci 2020;41(1):51–60. https://doi.org/10.1080/02522667.2020.1714183.
[222] Hong T, Lee M, Koo C, Jeong K, Kim J. Development of a method for estimating the rooftop solar photovoltaic (PV) potential by analysis the available rooftop area using Hillshade analysis. Appl Energy 2017;194:320–32. https://doi.org/10.1016/j.apenergy.2016.07.001.
[223] Bodis K, Kougias I, Jager-Waldau A, Taylor N, Szabo S. A high-resolution geospatial assessment of the rooftop solar photovoltaic potential in the European Union. Renew Sustain Energy Rev 2019;114:109309. https://doi.org/10.1016/j.rser.2019.109309.
[224] Singh R, Banerjee R. Estimation of rooftop solar photovoltaic potential of a city. Sol Energy 2015;115:589–602. https://doi.org/10.1016/j.solener.2015.03.016.
[225] Vulkan A, Kloog I, Dorman M, Erell E. Modeling the potential for PV installation in residential buildings in dense urban areas. Energy Build 2018;169:97–109. https://doi.org/10.1016/j.enbuild.2018.03.052.
[226] Hafeznia H, Yousefi H, Astaraei FR. A novel framework for the potential assessment of utility-scale photovoltaic solar energy, application to eastern Iran. Energy Convers Manage 2017;151:240–58. https://doi.org/10.1016/j.enconman.2017.08.076.
[227] Jamal T, Ongsakul W, Singh JG, Salehin S, Ferdous SM. Potential rooftop distribution mapping using geographic information systems (GIS) for solar PV installation: a case study for Dhaka, Bangladesh. In: 2014 3rd international conference on the developments in renewable energy technology (ICDRET); 2014. DOI: 10.1109/ICDRET.2014.6861648.
[228] Jakubiec J-A, Reinhart CH. A method for predicting city-wide electricity gains from photovoltaic panels based on LiDAR and GIS data combined with hourly DaySIM simulations. Sol Energy 2013;93:127–43. https://doi.org/10.1016/j.solener.2013.03.022.
[229] Song X, Huang Y, Zhao C, Liu Y, Lu Y, Chang Y, et al. An approach for estimating solar photovoltaic potential based on rooftop retrieval from remote sensing images. Energies 2018;11(11):3172. https://doi.org/10.3390/en11113172.
[230] Liang J, Gong J, Zhou J, Ibrahim AN. An open-source 3D solar radiation model integrated with a 3D geographic information system. Environ Modell Software 2015;64:94–101. https://doi.org/10.1016/j.envsoft.2014.11.019.
[231] Dehwah AHA, Asif M, Rahman MT. Prospects of PV application in unregulated building rooftops in developing countries: a perspective from Saudi Arabia. Energy Build 2018;171:76–87. https://doi.org/10.1016/j.enbuild.2018.04.001.
[232] De Vries TNC, Bronkhorst J, Vermeer M, Donker JCB, Briels SA, Ziar H, et al. A quick-scan method to assess photovoltaic rooftop potential based on aerial imagery and LiDAR. Sol Energy 2020;209:96–107. https://doi.org/10.1016/j.solener.2020.07.035.
[233] Yang Y, Campana PE, Stridh B, Yan J. Potential analysis of roof-mounted solar photovoltaics in Sweden. Appl Energy 2020;279:115786. https://doi.org/10.1016/j.apenergy.2020.115786.
[234] Lukac N, Spelic D, Stumberger G, Zalik B. Optimization for large-scale photovoltaic arrays' placement based on light detection and ranging data. Appl Energy 2020;263:114592. https://doi.org/10.1016/j.apenergy.2020.114592.
[235] Jurasz JK, Dabek PB, Campana PE. Can a city reach energy self-sufficiency by means of rooftop photovoltaics? Case study from Poland. J Cleaner Prod 2020;245:118813. https://doi.org/10.1016/j.jclepro.2019.118813.
[236] Assouline D, Mohajeri N, Scartezzini J-L. A machine learning methodology for estimating roof-top photovoltaic solar energy potential in Switzerland. In: Proceedings of international conference CISBAT; 2015: 555–60. Doi: 10.5075/epfl-cisbat2015-555-560.
[237] Assouline D. Machine learning and geographic information systems for large-scale mapping for renewable energy potential. EPFL, Thesis 2019: 1-247 https://actu.epfl.ch/news/new-phd-dan-assouline-ai-sees-potential-for-rene-2/.
[238] Walch A, Castello R, Mohajeri N, Scartezzini J-L. A fast machine learning model for large-scale estimation of annual solar irradiation on rooftops. In: Proceedings of solar world congress; 2019. doi:10.18086/swc.2019.45.12.
[239] Walch A, Castello R, Mohajeri N, Scartezzini J-L. Big data mining for the estimation of hourly rooftop photovoltaic potential and its uncertainty. Appl Energy 2020;262:114404. https://doi.org/10.1016/j.apenergy.2019.114404.

[240] Lee M, Hong T. Hybrid agent-based modeling of rooftop solar photovoltaic adoption by integrating the geographic information system and data mining technique. Energy Conserv Manage 2019;183:266–79. https://doi.org/10.1016/j.enconman.2018.12.096.
[241] Mainzer K, Fath K, McKenna R, Stengel J, Fichtner W, Schultmann F. A high-resolution determination of the technical potential for residential-roof-mounted photovoltaic systems in Germany. Sol Energy 2014;105:715–31. https://doi.org/10.1016/j.solener.2014.04.015.
[242] Fonseca JA, Nguyen T-A, Schlueter A, Marechal F. City Energy Analyst (CEA): integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts. Energy Build 2016;113:202–26. https://doi.org/10.1016/j.enbuild.2015.11.055.
[243] Mainzer K, Killinger S, McKenna R, Fichtner W. Assessment of rooftop photovoltaic potentials at the urban level using publicly available geodata and image recognition techniques. Sol Energy 2017;155:561–73. https://doi.org/10.1016/j.solener.2017.06.065.
[244] Bradbury K, Saboo R, Johnson TL, Malaf JM, Devarajan A, Zhang W, et al. Distributed solar photovoltaic array location and extent dataset for remote sensing object identification. Sci Data 2016;3:160106. https://doi.org/10.1038/sdata.2016.106.
[245] Joshi B, Hayk B, Al-Hinai A, Woon WL. Rooftop detection for planning of solar PV deployment: a case study in Abu Dhabi. In: Data analysis for Renewable Energy Integration, Conference Proceedings, Springer; 2014: 137–49. DOI: 10.1007/978-3-319-13290-711.
[246] Khandakar A, Chowdhury MEH, Kazi M-K, Benhmed K, Touati F, Al-Hitmi M, et al. Machine learning based photovoltaics (PV) power prediction using different environmental parameters of Qatar. Energies 2019;12(2782):1–19. https://doi.org/10.3390/en12142782.
[247] Huang Z, Mendis T, Xu S. Urban solar utilization potential mapping via deep learning technology: a case study of Wuhan, China. Appl Energy 2019;250:283–91. https://doi.org/10.1016/j.apenergy.2019.04.113.
[248] Rumbayan M, Abudureyimu A, Nagasaka K. Mapping of solar energy potential in Indonesia using artificial neural network and geographical information system. Renew Sustain Energy Rev 2012;16:1437–49. https://doi.org/10.1016/j.rser.2011.11.024.
[249] Anwar K, Deshmukh S. Assessment and mapping of solar energy potential using artificial neural network and GIS technology in the southern part of India. Int J Renew Energy Res 2018;8(2):974–85. https://www.ijrer.org/ijrer/index.php/ijrer/article/view/7674.
[250] Yadav AK, Chandel S-S. Solar energy potential assessment of western Himalayan Indian state of Himachal Pradesh using J48 algorithm of WEKA in ANN based prediction model. Renew Energy 2015;75:675–93. https://doi.org/10.1016/j.renene.2014.10.046.
[251] Rabbi KM, Nandi I, Saleh AS, Faisal F, Mojumder S. Prediction of solar irradiation in Bangladesh using artificial neural network (ANN) and data mapping using GIS technology. In: 2016 4th international conference on the development in the renewable energy technology (ICDRET). IEEE; 2016:15821764. Doi: 10.1109/ICDRET.2016.7421482.
[252] Li Z, Zhang Z, Davey K. Estimating geographical PV potential using LiDAR data for buildings in Downtown San Francisco. Trans GIS 2015;19(6):930–63. https://doi.org/10.1111/tgis.12140.
[253] Mohajeri N, Assouline D, Guiboud B, Scartezzini J-L. Does roof shape matter? Solar photovoltaic (PV) integrating on building roofs. In: Proceedings of the international conference on sustainable built environment (SBE) June 15-17; 2016. https://infoscience.epfl.ch/record/220006.
[254] Mohajeri N, Assouline D, Guiboud B, Scartezzini J-L. Effects of city size on the large-scale decentralised solar energy potential. Energy Procedia 2017;122:697–702. https://doi.org/10.1016/j.egypro.2017.07.372.
[255] Assouline D, Mohajeri N, Scartezzini J-L. Building rooftop classification using random forests for large-scale PV deployment. In: Conference of Earth Resource Environment Remote Sensing/GIS Applications Vlll 2017;10428:1042806. Doi: 10.1117/12.2277692.
[256] Vartholomaios A. A machine learning approach to modelling solar irradiation of urban and terrain 3D models. Comput, Environ Urban Syst 2019;78:101387. https://doi.org/10.1016/j.compenvurbsys.2019.101387.
[257] Fadare DA. Modelling of solar energy potential in Nigeria using an artificial neural network model. Appl Energy 2009;86:1410–22. https://doi.org/10.1016/j.apenergy.2008.12.005.
[258] Koo C, Hong T, Lee M, Park HS. Estimation of the monthly average daily solar radiation using geographic information system and advanced cased case-based reasoning. Environ Sci Technol 2013;47:4829–39. https://doi.org/10.1021/es303774a.
[259] Walch A, Castello R, Mohajeri N, Guignard F, Kanevski M, Scartezzini J-L. Spatio-temporal modelling and uncertainty estimation of hourly global solar irradiance using extreme learning machines. Energy Procedia 2019;158:6378–83. https://doi.org/10.1016/j.egypro.2019.01.219.
[260] Loutzenhiser PG, Manz H, Felsmann C, Strachan PA, Frank T, Maxwell GM. Empirical validation of models to compute solar irradiance on inclined surfaces for building energy simulation. Sol Energy 2007;81:254–67. https://doi.org/10.1016/j.solener.2006.03.009.
[261] Rhap VM, Huong NT-T, Hanh PT, Duy P-V, Binh DV. Assessment of rooftop solar power technical potential in Hanoi city, Vietnam. J Build Eng 2020;32:101528. https://doi.org/10.1016/j.jobe.2020.101528.
[262] Takebayashi H, Ishii E, Moriyama M, Sakaki A, Nakajima S, Ueda H. Study to examine the potential for solar energy utilization based on the relationship between urban morphology and solar radiation gain on building rooftops and wall surfaces. Sol Energy 2015;119:362–9. https://doi.org/10.1016/j.solener.2015.05.039.
[263] Motevalli A, Pourghasemi HR, Zabihi M. Assessment of GIS-based machine learning algorithms for spatial modeling of landslide susceptibility: case study in Iran. Comprehensive Geogr Inform Syst 2018:258–80. https://doi.org/10.1016/B978-0-12-409548-9.10461-0.
[264] Howlader M, Howlader M, Rokonuzzaman, Khan S-A, Nur A U, Al Amin A. GIS-based solar irradiation forecasting using support vector regression and investigations of technical constraints for PV deployment in Bangladesh. In: Proceedings of the 2017 4th international conference on advances in electrical engineering. IEEE; 2017: 675–80. DOI: 10.1109/ICAEE.2017.8255441.
[265] Kaygusuz K. Prediction of the solar photovoltaic potential for electricity generation in Turkey. J Eng Res Appl Sci 2019;8(2):1271–8. https://journaleras.com/index.php/jeras/article/view/182.