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Determination of the urban rooftop photovoltaic potential: A state of the art

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Abstract

In today's world, the necessity of reducing greenhouse gas emissions to meet the global warming regulations has increased the demand for renewable energy sources. A notable portion of energy consumption is dedicated to urban environments. While solar energy is the most promising sustainable energy, urban environments can be considered as high-potential electricity producers by using rooftop-mounted photovoltaic systems. However, effective guidelines for optimal installation of solar photovoltaics remains a challenge. Although in recent years there has been a vast development of methods as well as improvement in availability of data sources. Since it is not always possible to apply the same techniques, specific approaches are needed for local, regional, or continental scales. It still remains to develop a uniform accurate multi-factor method that uses uniform open data sources to determine urban rooftop's photovoltaic potential. The aim of this paper is to make a complete systematic review of various developed methodologies published in the current state of the art, and identify vital factors for urban rooftop solar photovoltaic potential assessment as well as to detect the best available methods to create a complete global basis for future studies.

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Keywords: Photovoltaic potential; Solar photovoltaics; Large-scale solar potential; LIDAR; GIS; Machine learning

1. Introduction

Due to the energy crisis and environmental degradation [1], determining the renewable energy potential has an essential aspect in energy policies and regulation developments [2]. At present, urban environments accommodate more than 50% of the world's population, and by the year 2050, it is estimated to reach 70% due to the rise of urban area migration. The result is the growth of cities' energy demand which is expected to be 75% of global energy consumption, by 2030 [1]. While the cities have a significant share of energy consumption, they can also be

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Nomenclature

DRAPE	Digital Raster Acquisition Project-East
GIS	Geographic Information Systems
LiDAR	Light Detection and Ranging
MSG	Meteosat Second Generation
PV	Photovoltaic
PVGIS	Photovoltaic Geographic Information Systems
SVM	Support Vector Machine
UAS	Unmanned Aerial Systems
SVR	Support Vector Regression

considered high-potential energy producers. So, an effective solution for urban energy management to solve urban energy requirements, as well as environmental issues, is the use of rooftop solar photovoltaics [1].

Urban building rooftops provide promising locations for solar photovoltaic installations. However, an efficient methodology for obtaining the roof solar energy potential by determining suitable roofs for optimal installation of solar photovoltaics remains a challenge [3]. The research for optimal photovoltaic (PV) installation has begun to make progress mostly in developed European and American counties, however, there is a lack of solar energy production potential maps for future solar urban planning [1]. One of the most important aspects of determining rooftop photovoltaics potential is the size of the study area [4]. Due to the lack of data diversity in some regions, the high cost of accessing the data sources, and time-consuming procedures, applying the same techniques are frequently not possible at local, regional, or continental scales.

So, this study aims to review and compare the various methodologies available for determining the urban rooftop PV potential and find the best available methods to create a complete global basis for future researches. The structure of the presented paper is as follows: Section 2 introduces different affecting factors and data sources. Section 3 presents the different methodologies for determining the urban rooftop PV potential and their practical contribution. Section 4 shows different methodologies information in the form of a table to form a better outlook for future studies and applications. Section 5 states the conclusion.

2. Affecting factors and data sources

One of the earliest projects for determining solar photovoltaic potential was Solar Urban Planning Berlin from 2004 [5]. The project aimed to conduct a multi-factor evaluation, however, it failed to evaluate the overall solar photovoltaic utilization potential of the city due to the technical limitations at that time [1]. Since that time with the dramatic development of technology, there are many more attempts to determine the solar photovoltaic potential, however, the selection of variables strongly depends on the project scales and data availability. Overall, regardless of the methodologies and project scales, different sub-potentials must be determined and studied in order to find the optimal points which are the desired rooftop photovoltaic potential. Fig. 1 presents the overview of these sub-potentials which are described as follow:

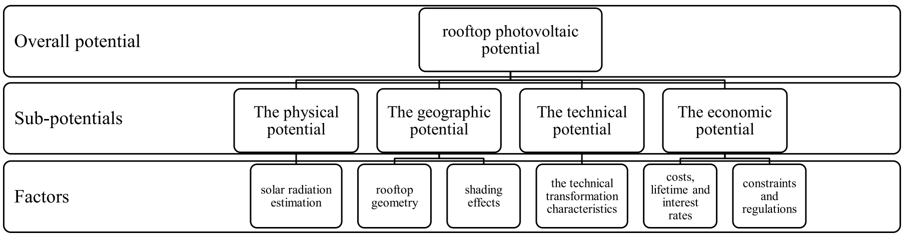

Fig. 1. An overview of rooftop photovoltaic potential essential factors.

1—The first sub-potential is the resource's maximum energy limit which encompasses the sun's total energy received by the urban areas (physical potential) [2,6]. Most of the considered factors for solar radiation estimation are related to meteorological data e.g. the monthly radiation, monthly clearness index [2].

2—The second sub-potential that must be evaluated is the impact of the built environment and the location constraints (the geographic or urban potential) [6,7]. The overall renewable resources geographical potential is usually determined by excluding reserved zones such as roads, beaches, rivers and lakes, and protected areas such as National Parks. Due to the purpose of the project which is determining the available roof area for photovoltaic installations to capture the solar energy, these exclusion criteria are meaningless [2]. Instead, the geographical potential expresses attempts to find suitable rooftops to install photovoltaics considering the essential factors such as the rooftop geometry, other buildings and trees shading effects, superstructures located on rooftops, rooftops inclinations, and rooftops slopes [6,7].

3—The maximum electricity production from a particular renewable energy technology considering the technical characteristics [8] is the third sub-potential (The technical potential or the potential electricity generation) [7]. To transform the solar energy received by the available roof area into electrical energy, the sub-potential is calculated by taking into account the technical transformation characteristics of the solar photovoltaic technology such as the efficiency and the performance [6]. The performance ratio is the difference between standard test conditions performance and the actual output of the system [9] which occurs due to the deviation from standard test conditions, and the losses of panel mismatch, dirt, cables, and inverters [6]. In addition to the technical characteristics of photovoltaics, the space needed between photovoltaic modules to avoid shadowing is another important aspect of determining the technical potential [2].

4—For a complete realistic potential assessment, additional sub-potentials should be considered (The social potential, The economic potential, the market potential) [2,10]. These potentials include economical parameters such as installation costs, maintenance costs, installation lifetime, interest rate [11], operational cost [7], as well as cost constraints, societal constraints, and government regulations [10]. The rooftop photovoltaic installation's economic attractiveness under current market conditions must be investigated to determine the profitability of a specific location [12]. Due to complexity, such analyses are not included in most papers and considered beyond the scope of the study [8], while building's owners will only consider investing on rooftop photovoltaic installations when these facilities are economically justifiable [12].

There are some suggestions for economic factor involvements, such as the development of a technical and economic potential by considering the maximum technical potential and combining it with economic factors [7]. Besides, due to the uncertainly of the decision-making environment, projects interactions factors as well as the need of maximizing the benefit and installed capacity, individual framework analyses are being developed in recent years to assess economic potential [13]. Economy criteria such as resource, risk factor, and engineering feasibility were also established based on industrial and commercial rooftop Photovoltaic projects [14].

One of the essential steps of determining the urban PV potential is defining the data sources and their availability. Meteorological data can be obtained from ground-based meteorological stations [8], Meteosat Second Generation satellite observations [15], or by using different solar models to calculate the needed data from other available data sources [8]. Satellite data is preferable to measurement station data due to the better spatial coverage, increased resolution, and very low missing data ratio ($<1\%$) [7,15]. Alongside the meteorological data, regarding the methodologies and project scales, different data sources must be used and studied in order to find the desired rooftop photovoltaic potential. For example, the Statistical Institutions can present the number of buildings and the population in the urban areas [2], statistical construction data [16], the Corine Land Cover database presents the urban land use, cadastral database [2], LiDAR data [3,6], GIS data [2,11] which can be modified using ArcGIS tools [6,17–20], and Google satellite images [1] or digital urban maps obtained from Google Earth™ [16].

3. Methodologies

The technical potential estimation of roof-integrated photovoltaic systems for Spain's urban areas was done based on a statistically representative stratified-sample of vector GIS maps, and data such as land uses and building densities. The mean available photovoltaic installation area was calculated with a 95% confidence level and the error of $\pm 32\%$ by stratified statistical sampling as a finite set of average building typologies function in every urban area of the study region [2]. This method was also used as a basis to quantify the amount of thermal and electrical energy by the installation of solar hot water systems and photovoltaic systems in Spain to produce a quantitative picture of the possible limitations of roof-top solar energy [11].

The energy capacity of grid-connected photovoltaic on building rooftops was determined with a stratified sampling technique using statistical construction data, and Google Earth™ digital urban maps exported and scaled with the AutoCAD®. The mean roof surface was determined with 95% confidence level and the sample error margin of 10% taking into account data such as building type, orientation, roof tilt angle, location, and shading. The maximum residential rooftop photovoltaic potential in Andalusia (Spain) was calculated for two different roof types which could satisfy 78.89% of energy demand, and external energy dependence reduction to 21.02% [16]. Photovoltaic solar potential over the Piedmont region (Italy) was proceeded by a hierarchical methodology. Raster maps and the Numerical Technical Regional maps were used for solar radiation and geographical–cadastral analysis respectively which were analyzed by ArcGIS® and processed in MATLAB®. Worth mentioning that roof type topology is assumed to be double-pitched and only one of two pitches is considered for module installation. Shadowing effect of tall building is assumed as a coefficient of 0.46 due to the lack of 3D city modeling.

In the case of energy production, three different scenarios with different technologies were measured that may reach 6.9 TWh [21]. According to the previous methodology, a new algorithm based on aerial georeferenced images was developed in MATLAB® to determine the available roof area of Turin. The proposed algorithm was able to calculate roof availability, shadows, pitch brightness, and angle of the installations. A mean accuracy error of 10% on overall results was stated. In comparison with previous work, the available roof area can be 41% higher and the photovoltaic potential increase from 508 to 719 GWh [22].

A quick-scan method was used to determine rooftop photovoltaic potential in Eindhoven (Netherlands) by reconstructing virtual 3D roof segments and developing a fitting algorithm for photovoltaic modules on rooftops. Aerial imagery, weather, GIS, and LIDAR data were used as input data. Solar Monkey, photovoltaic GIS, and photovoltaic material and devices were used to calculate the annual rooftop potential. Results presented relative standard deviations of 7.2%, 9.1%, and 7.5% respectively [23]. A comparison of rooftop solar energy potential estimation by UAS and LiDAR data was carried out. ArcGIS solar analysis toolbox was used to determine the rooftop solar radiation. Results indicated 36% improvement for aggregate irradiation estimation by using UAS compared to LiDAR [24].

A combination between LiDAR data, pyranometer measurements of solar irradiances, a Heuristic vegetation shadowing and multi-resolution shadowing model was proposed in Maribor (Slovenia). This methodology implemented the roof surfaces rating based on their solar potential and sustainability for photovoltaic systems installation. A comparison between the proposed method and actual measurements showed a difference of 2.6% [25]. Also, a nonlinear PV potential estimation by using LiDAR data was presented in Maribor (Slovenia), considering different influential factors such as topography, vegetation, and shadowing which had a key role in the accuracy of the proposed method. The results of a comparison between constant and nonlinear efficiency characteristics of solar inverters and PV module types showed that largest difference detected during summer [19].

An estimation of Photovoltaic potential in Lisbon (Portugal) was conducted by using LiDAR data, population distribution, and ArcGIS solar analyst extension tool. The result stated that rooftop potential of 538 identified buildings was about 11.5 GWh that can supply 48% of local energy demand. It is noted that by choosing the photovoltaic location carefully, 10% of the available area can collect 13% of available energy [20].

Extraction algorithms combined with PV system simulations were proposed to determine rooftop photovoltaic potential in Stuttgart (Germany) by using geoinformation systems, 3D model and LiDAR data. Results showed the ratio of total PV energy production and the total electricity consumption was 35% [26].

An evaluation of the potential contribution of rooftop PV to the future electricity mix in Spain carried out using ArcGIS and the national geographical database, considered five sustainable scenarios each comprising different shares of centralized renewables, rooftop PV and storage. The results stated that a sustainable electricity system at a lower cost than current wholesale market prices providing up to nearly 45% of the demand, is possible for Spain [27]. Cost-optimal economic potential was calculated in Austria for Rooftop photovoltaic systems by an optimization model and settlement patterns. The cost-optimal economic rooftop PV potential on a large scale was estimated by upscaling.

Different sensitivity analyses were also conducted by taking into account the electricity prices, distribution grid tariff structures, and photovoltaic system cost. The results stated that the photovoltaic capacity would meet the Austrian 2030 policy goal of a 100% renewable electricity generation [28]. A methodology for calculating the building roofs and façade's economic potential for Photovoltaic installation in Karlsruhe (Germany) was proposed. To simulate solar irradiation, the validated lighting simulation tool radiance was applied to 3D city model. It is concluded that facades almost have a triple area in comparison with roofs, however, they only receive 41% of total irradiation due to their non-optimal inclination and orientation [12].

A methodology for determining Photovoltaic potential at regional and urban scale of Ludwigsburg (Germany) was developed by using CityGML geometry description and 3D models for simulations, analyses, and visualization on SimStadt platform. Emission assessment, economic and technical potential as well as two different efficiency scenarios of Photovoltaic, wafer-based silicon modules and thin-film modules, were investigated. It has concluded that by using all available roof space, 77% of the region's energy demand could be covered [29].

Rooftop solar photovoltaic potential in Ontario (Canada) was determined by five essential steps. Alongside GIS data, Census data, Municipalities roof print data, Digital Raster Acquisition Project-East, population, population density, and land area were used. The Feature Analysis extraction tool in ArcGIS was applied for obtaining roof areas with a 95% confidence level and an error of 15% on each data point of population. A more accurate energy modeling by considering an analysis in structures shading and orientation was suggested to increase the accuracy [30]. By using GIS and LiDAR data, a multi-criteria approach for rooftop photovoltaic potential estimating in Lethbridge (Canada) was developed, and an economic assessment by utilizing market prices was conducted which determined economically feasibility of 96% of available rooftops. It is achieved the photovoltaic energy production of about 301 GWh with a total uncertainty of 9.5%, which can cover 38% of the annual electricity demand [8].

A method was developed to predict photovoltaic potential over 17000 rooftops for Cambridge (USA) based on combination of 3D models, GIS and LiDAR with Daysim irradiation simulation engine, rooftop temperature, and meteorological climate data. The outcome can combine by online mapping and financial modules to interest the potential building owners for installing photovoltaic panels on buildings. The result noted that predicted energy production was 3.6% and 5.3% less than actual measured energy production in the student center and the residential zone respectively [31].

Residential rooftop solar potential was detected in Erie County (USA) by using remote sensing, LiDAR, footprint, and Google's Project Sunroof data. Worth mentioning, Digital Terrain Model, Digital Surface Model, and normalized Digital Surface Model, generated using the LiDAR data. Results indicated that low income population had relatively low access to rooftop solar as well as limited access to potential community solar sites [32].

A generated electricity estimator of a photovoltaic system in the northern, southern, and central parts of South Korea was developed. The results of sensitivity analysis on impact factors by using an energy system, GIS, and genetic algorithm, showed 1.12, 1.37, and 1.62 fold differences in annual electricity generation based on regional factor, the slope, and the azimuth of the installed panel respectively [33]. Due to the high impact of shadowing factor on determining available roof area, an estimation method was proposed for photovoltaic system in Seoul (South Korea) to analyze building shadowing by using Hillshade analysis, and rooftop area estimation was 4,903,079 m^2 [34]. Based on the previous method, an estimation of rooftop solar potential was proposed with improvements such as considering localized characteristics of rooftop on macro-scale, and changing sun location. It was concluded that in Gangnam district of Seoul, the monthly physical photovoltaic potential at noon was varied from 79,117 MWh to 147,222 MWh while physical and technical potential were 9,287,982 MWh and 1,130,371 MWh respectively [35].

The development potential of rooftop photovoltaic technologies along with their environmental benefit was investigated in Hong Kong. The rooftops installation capacity potential for photovoltaic systems and annual energy output were estimated as 5.97 GW_p and 5981 GWh respectively with an error rate of 10%–15%. Encompassing 14.2% of the total electricity demand in Hong Kong. Also, approximately 3,732,000 t of greenhouse gas emissions reduction was estimated [36].

A digital surface model containing topography, building, and trees of Auckland (New Zealand) was developed by using LiDAR data. Solar radiation tool in ArcGIS was used with the model, and for policy insights, census data such as household income and average number of residents was used to obtain financial potential as well as electricity demand of neighborhood, but there is still a need of developing individual houses and market models [37].

Residential solar rooftop potential was presented in Riyadh (Saudi Arabia), to assess the cost-efficiency, by combining two different methodological approaches, namely standard Leverage cost of electricity approach, and nightlight intensity methodology. The results showed that even assuming aggressive reductions in the investment cost of solar technology, rooftop solar PV cannot compete with electricity from the grid due to the current residential electricity prices [38].

Rooftop solar system energy potential and economic performance of Khalifa and Zayed (Abu Dhabi) were estimated. Number of buildings, their types, and rooftop area were calculated by Esri ArcGIS software. The result indicated that the capacity estimated in Khalifa would cover 11 to 20% of the annual electricity building's demand, however, It was economically infeasible which led to a policy suggestion for the government [39].

Mumbai (India) rooftop Photovoltaic potential was estimated by a methodology that used GIS image analysis, high-granularity land public data, and sunshine simulation in PVSyst. Results presented potential of 2190 MW which can provide 12.8%–20% daily demand as well as 31%–60% of morning peak demand [40]. The same methodology was also used as the based estimation with mathematical models and micro-level simulations in the PVSyst. Due to the lack of high-resolution urban building data, the focus was mainly on developing a workable estimation instead of an accurate one, and total photovoltaic potential of 13 Indian cities estimated about 17.8 GWp [41].

A merging national datasets methodology was developed to estimate rooftop solar potential, rooftop photovoltaic systems distribution, and socioeconomic and demographic characteristics for four US cities. ArcGIS software was used to map the total rooftop potential distributions, low and moderate-income market share, and total rooftop penetration for visual comparison. four regression models were also developed to explore the relationships between solar penetration and area-level socioeconomic and demographic characteristics [42].

A computational data-based Machine Learning methodology with GIS was used to estimate rooftop photovoltaic potentials for 1901 Switzerland's communes using LiDAR data, CORINE Land Cover data, Population density, and building residential typology. The supervised learning Support Vector Machine algorithm was used with 6-fold cross-validation and root-mean-square error. The results stated average value of 81% of each building's total ground floor area was equal to the Photovoltaic installation's available roof area, and the estimated energy production amount was 28% of Switzerland's electricity consumption [6]. Different shapes of building rooftop can also affect the overall rooftop photovoltaic potential. Six different types of rooftop shapes for 10,085 buildings in Geneva (Switzerland) were classified with Support Vector Machine classification. The combination of MATLAB® and solar radiation analysis tools in GIS as well as LiDAR data were also used. It was concluded that the lowest PV potential was for hip roofs, while the highest PV potential was for the flat and shed roofs. The useful roof area and the building footprint ratio was close to one for most of the roof shapes, and due to the availability of footprint areas, they can be used as approximate substitutes to assess useful roof areas for PVs [3]. A combination of GIS, solar models, and Random Forests Machine Learning algorithm using Digital Orthophoto Map and LiDAR data was presented to estimate the rooftop PV potential in Switzerland. The uncertainty of the estimations was measured by provided prediction Intervals for the different estimated variables. The result estimated 25.3% energy production of total electricity demand [10].

A data mining approach combining the Machine Learning algorithms, GIS, and physical models were applied to 9.6 million rooftops in Switzerland to address the lack of high-resolution data and the uncertainties related to existing processing methods. The results stated that the available roof area for photovoltaic installation was 55% of the total Swiss roof surface which could meet more than 40% of Switzerland's annual electricity demand. For direct validation, using image segmentation techniques such as Convolutional Neural Networks, to high-resolution aerial imagery for objects detection and already installed photovoltaic panels was suggested [7]. For instance, a supervised machine learning method based on convolutional neural networks was developed to use pixel-wise image segmentation on the Swiss high-resolution aerial photos for detecting the rooftop solar panels and to determine their sizes. Results indicated that accuracy of about 94% for a pixel-level set of solar panels was obtained [43].

Image segmentation with U-Net, a deep learning technology, was developed for detecting the solar photovoltaic potential of Wuhan (China) urban rooftops using a large range of open-source satellite imagery. The overall potential was calculated with an error of 9.51% considering the polycrystalline Silicon as photovoltaic panels [1]. Image recognition and machine learning approaches as well as economic analysis were used to determine the rooftop photovoltaic potential of Freiburg (Germany). A normal distribution function was used to estimate roof tilt while efficiency of the modules and the inverter system were simulated as a function of ambient temperature, irradiance and load factor. An algorithm that iterated over the usable area was used to fit as many photovoltaics as possible, and a CNN algorithm was proposed to detect roofs with already photovoltaic installations. The results showed an accuracy of about 70% for roof azimuth estimation, and an accuracy of about 90% for detecting existing solar installations [44].

To address challenges of policy and electricity system planning level of EU, a geospatial methodology was developed that combined statistical and satellite-based data sources with machine learning to assess technical potential across EU considering the cost of electricity. It predicted production of 680 TWh equal to 24.4% of energy demand [45].

The rooftop solar technical potential was determined in Hanoi (Vietnam) from the energy supply perspective by using GIS, and high-resolution satellite image analysis technology, combining with artificial intelligence algorithms. The method consists of identifying and classifying rooftops, determining suitable rooftop's surface area for photovoltaic installation, and evaluating overall potential with help of Digital Surface Model, Digital Height Model, and Digital Terrain Model. The total generated electricity of rooftop solar power was estimated 37,591,481 MWh [46].

Based on obtaining rooftop features from remote sensing images, an approach to predict Photovoltaic potential was developed in Beijing (China) in order to simulate rooftop solar radiation. These rooftop features included 2D outlines rooftop extracted from google maps with a precision of 87% by object-oriented classification method and Hough transformation. 3D rooftop parameters obtained from the digital surface model of Pleiades satellite. These features were calculated for five different types of rooftops. Finally, after calculating non-shadowed area and angle correction factor, a Photovoltaic potential of 63.78 GWh was measured [47].

4. Visual comparison of different methodologies

A visual comparison of available information from previous studies has been made in Table 1 which has a vital role in facilitating a complete systematic review as well as providing a comprehensive global basis for future studies. Some studies implement statistical as well as physical models for assessing the photovoltaic solar energy potential, and computational Machine Learning methodologies are used in recent years due to the development of technology. One of the vital data to find rooftop Photovoltaic potential is meteorological data, and due to the obvious usage of this data it is not mentioned in Table 1. Statistical data also represents the data obtained statistically such as population, building density, national dataset, census information and municipalities dataset. Worth mentioning, error rates depend on methodology, data accuracy, and validation method.

Although there are various methods to determine the urban photovoltaics potential shown in Table 1, these methods frequently follow the same path shown in Fig. 2. Overall, studies tend to find the sub-potentials to determine the overall potential. The three steps of finding the physical potential, geographical potential, and technical potential are called the hierarchical methodology in most of the studies.

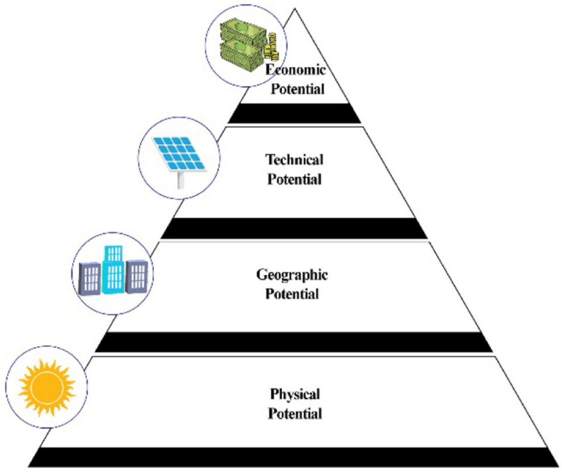

Fig. 2. Rooftop photovoltaic potential determination.

5. Conclusions

Urban environments can be considered as high-potential electricity producers using rooftop-mounted photovoltaic systems. Factor selection strongly depends on the project scales and data availability, so the same techniques are frequently not possible in different scales. However, with the development of technology and improvement in data accessibility, there are attempts to fulfill this gap by advanced modeling as well as artificial intelligence. This paper aims to make a complete systematic review for introducing different affecting factors and data sources. Moreover, it presents different methods to determine urban rooftop photovoltaic potential in order to create a complete global basis for future studies and applications. A visual comparison of available information has been made in Table 1 which has a vital role in facilitating a complete systematic review. It points out the consensus of the previous studies

Table 1. Different methodologies visual comparison.

Ref	Tools & Method	Data	Location	Location area (km^2)	Roof area (km^2)	Annual generated electricity	Demand coverage(%)	Error(%)	Year
[2]	Statistical stratified sampling	GIS-Statistical	Spain	505,990	571			32	2008
[16]	Statistical sampling	Google Earth-Statistical	Andalusia (Spain)	87,597	265.52	9.73 GWh	78.89	10	2010
[21]	Digital Elevation Modeling -MATLAB and GIS Software	GIS-Statistical	Piedmont (Italy)	25,000	43	6900 GWh	28.16	1.7	2011
[22]	Ortho-image analysis	Georeferenced images	Turin (Italy)			858 GWh		10	2011
[23]	quick-scan yield prediction	Aerial imagery-GIS-LIDAR	Eindhoven (Netherlands)	145 rooftop	145 rooftop	1070 kWh/kWp			2020
[24]	Digital elevation model	UAS-LIDAR	Phoenix (U.S)	0.265	0.027	5089 GWh			2020
[25]	Rating rooftops - Digital elevation model	LiDAR geospatial	Maribor (Slovenia)	1				2.6	2013
[19]	nonlinear efficiency characteristics model	LIDAR	Maribor (Slovenia)	0.5				12	2014
[20]	ArcGIS solar analyst extension tool	LIDAR- Statistical	Lisbon (Portugal)		538 rooftop	11.5 GWh	48		2012
[26]	modular simulation INSEL - 3D model	LIDAR	Stuttgart (Germany)	1.5			35		2012
[27]	Interpolation algorithm with Matlab - ArcGIS - PVGIS	National geographical - Cartographical	Spain	505,990	1134	291 TWh	45		2020
[28]	optimization model	statistical	Austria			10 GWp	100		2020
[12]	simulating solar irradiation - 3D city model - ArcGIS	Meteorological - 3D Model	Karlsruhe (Germany)	173		930 GWh			2015
[29]	3D model - SimStadt platform	solar radiation INSEL model - CityGML geometry description	Ludwigsburg (Germany)	700	22.26	1318 GWh	77		2017
[30]	Feature analyst extraction in ArcGIS	GIS - statistical	Part of Ontario (Canada)	48,000	25	6909 GWh	5	15	2010
[8]	digital surface model - digital elevation model - calculate solar radiation using ArcGIS	LiDAR - GIS	Lethbridge (Canada)	124.3	2.73	3011 GWh	38		2019
[31]	3D model-Daysim simulation	GIS - LiDAR	Cambridge (USA)			4881.3 kWh		5.3	2013
[32]	Normalized Digital Surface Model-Digital Terrain Model-Digital Surface Model	LiDAR - Statistical - Google Project Sunroof	Erie County (USA)	271					2020
[33]	GIS-based optimization model	Statistical - on-site information	Seoul-Busan-Daejeon (South Korea)			275.33 kWh per panel (busan)			2014
[34]	Hillshade tool and Polygon to Raster tool from ArcGIS	Building elevation - Statistical	Gangnam-Seoul (South Korea)		4.903				2016
[35]	Hillshade tool from ArcGIS	Building elevation - Statistical	Gangnam-Seoul (South Korea)		4.964	1,130,371 MWh	150		2017
[36]	estimate rooftop from ground floor area	Statistical- on-site information	Hong Kong		54	5981 GWh	14.2	15	2013
[37]	Bottom-up digital surface model - solar radiation ArcGIS	LiDAR - statistical	Auckland (New Zealand)			1364 kWh/m2			2017
[38]	Nightlight intensity methodology	Statistical - Nighttime satellite images	Riyadh (Saudi Arabia)		185,000 roof	0.7 TWh			2020
[39]	GIS-based method using Esri ArcGIS software	digital building shape	Khalifa - Zayed (Abu Dhabi)	23 (Khalifa)	2 (Khalifa)	206 GWh (Khalifa)	20 (Khalifa)		2020
[40]	GIS image analysis - micro–macro synthesis	Statistical - Google earth	Mumbai (India)	458.27		2190 MW	20	19.4	2015
[41]	mathematical model - micro-level simulations in PVSyst	Statistical - land-use and building stock	13 Indian cities			17.8 GWp			2020
[42]	merging national datasets - GIS software	DeepSolar - Statistic	4 US cities		395,387 roof				2020
[6]	supervised learning Support Vector Machine algorithm	LiDAR - CORINE Land Cover -statistical	Switzerland	1901 communes	328	17.86 TWh	28		2017
[3]	Support Vector Machine classification - MATLAB and solar radiation GIS	LIDAR	Geneva (Switzerland)		66,811 roof				2018
[10]	Machine Learning algorithm Random Forest model	LiDAR - Digital Orthophoto Map	Switzerland	41,285	252	16.29 Twh	25.3		2017

(*continued on next page*)

on the use of meteorological data as well as statistical data. The previous studies also tend to find the sub-potentials discussed in Section 2 to determine the overall potential. worth mentioning, three steps of finding the physical potential, geographical potential, and technical potential are called the hierarchical methodology in most of the studies. Finally, this paper suggests the development of a uniform accurate multi-factor method that uses uniform high-resolution open data sources to determine urban rooftop's photovoltaic potential map on a global scale.

Table 1 (*continued*).

Ref	Tools & Method	Data	Location	Location area (km^2)	Roof area (km^2)	Annual generated electricity	Demand coverage(%)	Error(%)	Year
[7]	data mining - Machine Learning - physical models	LiDAR - statistical	Switzerland	9,600,000 rooftops	267	24 TWh	40		2019
[1]	U-Net - deep learning	Google Earth	Wuhan (China)	961		17.3 TWh		9.51	2019
[44]	Image recognition - machine learning	Geographical building - Aerial images	Freiburg (Germany)		49,573 building	524 GWh			2017
[45]	machine learning	Statistical - Satellite	EU			680 TWh	24.4		2019
[46]	Artificial intelligence-Digital Surface Model - Digital Height Model-Digital Terrain Model	Statistical - Satellite image	Hanoi (Vietnam)	3359	139.4	37,591 GWh			2020
[47]	Segmentation - Digital surface models - Hough transformation	Satellite image	Beijing (China)		0.678	63.78 GWh			2018

Declaration of competing interest

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

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