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Authors

Castellanos, S
Sunter, DA
Kammen, DM

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Rooftop solar photovoltaic potential in cities: how scalable are assessment approaches?

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Sergio Castellanos^{1,2,3,5} , Deborah A Sunter^{1,2} and Daniel M Kammen^{1,2,4}

¹ Energy and Resources Group, University of California, Berkeley, Berkeley, CA 94720, United States of America

² Renewable and Appropriate Energy Laboratory, University of California, Berkeley, Berkeley, CA 94720, United States of America

³ Berkeley Energy and Climate Institute, University of California, Berkeley, Berkeley, CA 94720, United States of America

⁴ Goldman School of Public Policy, University of California, Berkeley, Berkeley, CA 94720, United States of America

⁵ Author to whom any correspondence should be addressed.

E-mail: sergioc@berkeley.edu

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Abstract

Distributed photovoltaics (PV) have played a critical role in the deployment of solar energy, currently making up roughly half of the global PV installed capacity. However, there remains significant unused economically beneficial potential. Estimates of the total technical potential for rooftop PV systems in the United States calculate a generation comparable to approximately 40% of the 2016 total national electric-sector sales. To best take advantage of the rooftop PV potential, effective analytic tools that support deployment strategies and aggressive local, state, and national policies to reduce the soft cost of solar energy are vital. A key step is the low-cost automation of data analysis and business case presentation for structure-integrated solar energy. In this paper, the scalability and resolution of various methods to assess the urban rooftop PV potential are compared, concluding with suggestions for future work in bridging methodologies to better assist policy makers.

1. Introduction

In response to the dramatic cost reductions in solar energy and energy storage, the ease of building integration, and increasing climate change risks, mitigation strategies involving renewable energy deployment have recently gained substantial traction. One low-carbon technology that has seen exponential growth is solar photovoltaics (PV). PV deployment has grown by a factor of 40 in the last 10 years, and now comprises close to 300 GW of global installed capacity (Kurtz *et al* 2017), with growth projections pointing towards approximately 430 GW by 2020, as reported by the International Energy Agency (IEA) (2015).

Distributed PV has historically dominated the solar industry, as seen in figure 1. However, there remains a tremendous untapped potential for further deployment. In fact, the total technical generation potential for rooftop PV systems in the United States alone is estimated to be almost 40% of the of 2016 total national electric-sector sales (Gagnon *et al* 2016).

Some of the barriers that have hindered the development of distributed PV are, among others

(Margolis and Zuboy 2006, Strupeit and Palm 2016), the lack of awareness by final users and stakeholders, high levels of risk aversion, system performance concerns, and lack of suitable rooftop space for installations (Schwartz *et al* 2017), with the greatest hindrance perhaps being the combination of these barriers. Considerable research efforts have pursued understanding, addressing, and solving the multiple adoption barriers.

In the case of locating suitable rooftops, particular attention has been focused on urban areas for their high density of rooftops. As the world becomes more urban, with an expected influx of 2.5 billion people into urban areas by 2050 (Department of Economic and Social Affairs Population Division 2014), an increase in built infrastructure to support this influx is expected, rendering urban areas as critical venues for distributed PV deployment. Furthermore, Kammen and Sunter (2016) suggest that city-integrated PV could have the potential to satisfy the energy needs of most cities if current advanced laboratory-tested PV technologies are commercialized and become cost-competitive.

Past growth in distributed PV in urban areas has been highly policy-dependent, and future growth may

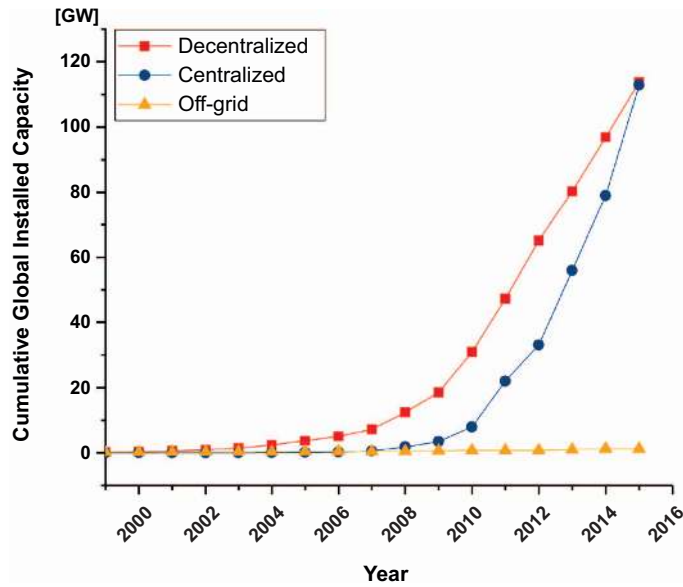


Figure 1. Evolution of cumulative global installed capacity (GW) from 2009–2015. The red line (squares) represents the cumulative capacity for decentralized grid-connected PV installations. The blue line (circles) represents centralized grid-connected PV systems. The yellow line (triangles) represents off-grid PV installations which, while small in capacity, are expected to continue growing (Lighting Global and Bloomberg New Energy Finance 2016) (International Energy Agency 2000, 2016).

be as well (Schwartz *et al* 2017). Identifying and accurately predicting PV potential, and communicating this potential to often risk-adverse nontechnical stakeholders is a challenge. Having accurate, accessible, and easily understood tools to assess distributed PV potential estimates is, therefore, an expected component for appropriate policy development.

The goal of this letter is to address the questions: *what is the reported scalability between rooftop PV assessment methods?* and *what is the expected deviation between reported methods of different spatial resolution?* from a policymaker's perspective, and via a comparative analysis of few cities. In this contribution, we focus solely on urban areas. We provide a framework to categorize methods to assess rooftop PV potential in cities, and evaluate the results amongst them. We first develop our framework by comparing a selection of reported assessment methods, and the tradeoffs between the amount of individual cities analyzed and their spatial resolution. Next, we compare results on PV rooftop potential from different methodologies to determine their variations on selected cities. Lastly, we conclude with suggestions for future work in bridging methodologies to better assist policy makers in their rooftop PV assessment efforts.

2. Methods

An initial assessment of review materials is performed using Google Scholar with keywords such as 'rooftop solar', 'PV rooftop assessment', 'GIS PV rooftop', 'PV rooftop potential', and permutations. Obtained results include peer-reviewed academic studies, conference proceedings, and professional reports from specialized agencies. Results are ordered by relevance and then broadened by analyzing the forward citations made

until the time of this publication. A narrowing down of the selected articles is then manually implemented by their relevance and application to cities, excluding country-wide, or region-wide aggregated results. This manual procedure may unintentionally omit some studies; therefore, this letter is an overview of a selection of methods and not an exhaustive review of all rooftop PV assessment research.

Reported PV potential estimates from literature are captured and categorized based on the spatial resolution of the techniques and reported results, and the cities covered in their contributions.

A methodological starting-point utilized by the IEA Energy Technology Perspectives report (2016) is to simply parameterize the rooftop PV potential by the population density and solar insolation. This approach estimates the total PV rooftop potential per city by first calculating the rooftop area per capita, A_{capita} , using the population density, ρ , as stated in equation (1). The constants in this equation (α with a value of 172.3, and β with a value of 0.352) were found by the IEA after performing a linear regression on 1600 cities with a correlation coefficient of 44% (IEA 2016)

$$A_{\text{capita}} = \alpha \cdot \rho^{-\beta} \quad (1)$$

Multiplying equation (1) by the total city population, P , gives the suitable roof area per city, A_{city} , as shown in equation (2),

$$A_{\text{city}} = A_{\text{capita}} \cdot P. \quad (2)$$

The total electricity generation potential $E_{\text{PV,IEA}}$ is then calculated, as shown in equation (3),

$$E_{\text{PV,IEA}} = A_{\text{city}} \cdot H_{\text{solar,city}} \cdot \eta \cdot PR \cdot f_{\text{orientation}} \quad (3)$$

where $H_{\text{solar,city}}$ is the solar insolation ($\text{kWh}^{-1} \text{m}^{-2} \text{yr}^{-1}$), η is the rooftop PV system efficiency, PR is the

performance ratio (assumed to be 75%, as indicated in (IEA 2016)), and $f_{\text{orientation}}$ is the orientation factor (assumed to be 1 in aggregate, as indicated in (IEA 2016)).

While equation (3) is very general and can be applied to any city to estimate the rooftop PV potential, many researchers have studied city-specific solutions. A selection of these city-specific solutions have been gathered both from literature and from online sources such as www.mapdwell.com (Mapdwell 2017) and *Google Project Sunroof* (Google 2017). To compare the city-specific solutions to the corresponding IEA solution, values for P , ρ , and η , used in equation (3), are consistent with those indicated in city-specific research methods. When these parameters are not specified, the PV system efficiency is assumed to be 15% and the population and population density are found using city-specific statistics (Italian National Institute of Statistics 2011, Korean Statistical Information Service 2010, Demographia 2016). The solar insolation, $H_{\text{solar,city}}$ for each city is acquired from NASA's Surface Meteorology and Solar Energy data (2014). The methods are then compared in terms of their total electricity generation potential from rooftop PV and their percent difference from the IEA method, where the percent difference, Δ , is calculated as follows:

$$\Delta = \frac{E_{\text{PV,IEA}} - E_{\text{PV,city-specific}}}{E_{\text{PV,IEA}}} \cdot 100\% \quad (4)$$

3. Results and discussion

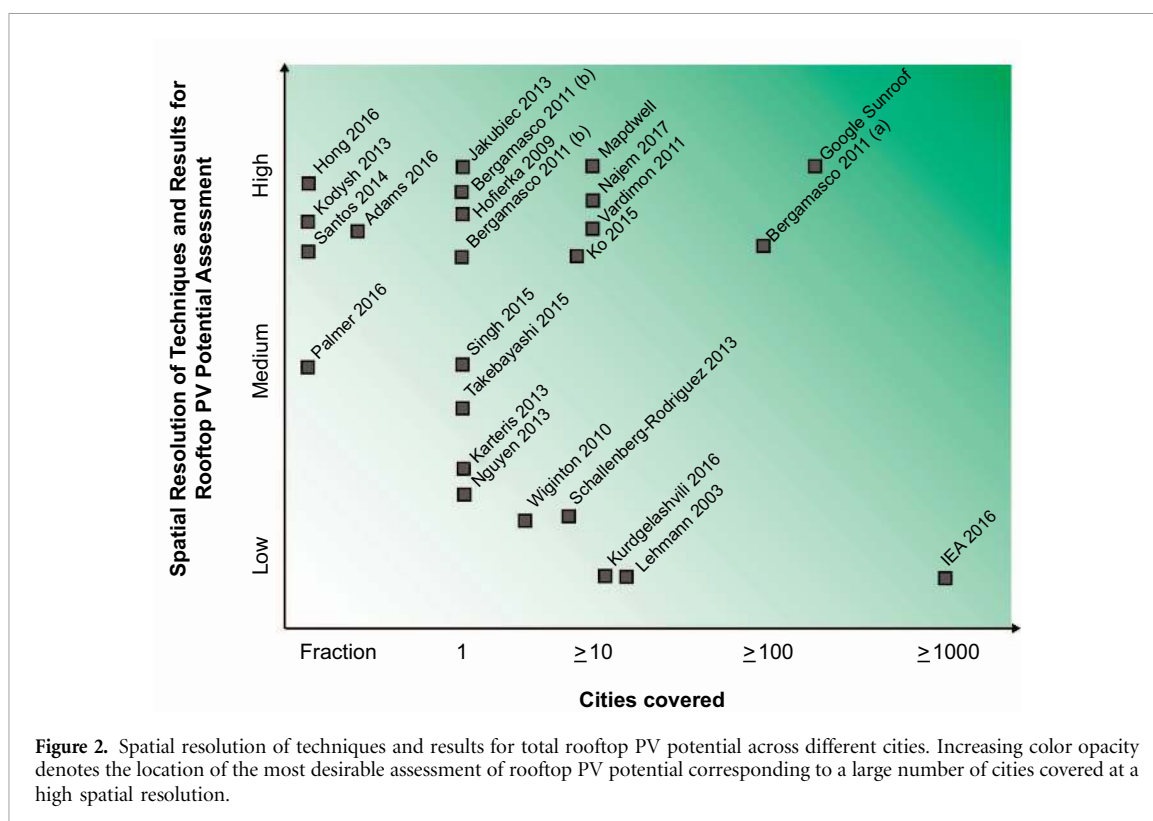
A simplified schematic of selected publications reporting rooftop PV assessment, somewhat similar in style to that reported by Mainzer *et al* (2014), is shown in figure 2. The schematic focuses solely on individual cities and the spatial resolution of the methodology used for the results presented in each work. A total of 24 publications are incorporated. The hierarchical methodology by Bergamasco and Asinari (2011a), in which the potential is categorized into physical, geographical, theoretical, and energy exploitation, are accounted for at different levels of detail to guide in this classification. The number of cities analyzed by a specific research method is represented in the x -axis: from a fraction (e.g. district, or city region) to multiple cities, and three broad categories in the y -axis described as 'low', 'medium', and 'high' categorize the spatial resolution of the techniques and results. A darker shade of green in the gradient-shaded background represents the optimal area to be located in the technique resolution-city coverage space: highly resolved rooftop PV potential technique that is applicable to many cities.

Low-level spatial resolution techniques and results are considered as those that rely mainly on aggregated statistical data that is assumed to be homogeneous throughout the city analyzed. An example is IEA's

approach described in the Energy Technology Perspectives report (2016) which aggregates statistical data from more than 1500 cities. Similar approaches in this category (Lehmann and Peter 2003, Kurdgelashvili *et al* 2016) correspond to regions where multiple German cities (extrapolated to Europe), and USA cities (with substantial state-level information), respectively, are evaluated on the basis of aggregated data. Similarly, other works fall in this level (Wiginton *et al* 2010, Schallenberg-Rodríguez 2013), and others begin to blend with medium-level classification results (Nguyen and Pearce 2013, Karteris *et al* 2013).

Medium-level category is herein defined as approaches that combine aggregated statistical data with spatially-resolved data acquired through geographical information systems (GIS) and light-detection-and-ranging (LiDAR) approaches. As an example, Singh and Banerjee (2015) mix high-granularity land use statistical data, GIS maps to calculate building footprint area, and couple these findings with PV system performance simulations to estimate rooftop PV potential in Mumbai, India. Cole *et al* (2016) perform a rooftop assessment methodology in Plymouth, UK, (which is extrapolated afterwards) by extracting 3D urban features from medium resolution LiDAR data, and combine with statistical scale-up methods from individual roofs within a segment of the city to apply to the entire UK. Similarly, by combining GIS data that is used in solar shading calculation routines, the rooftop PV potential in Osaka, Japan is assessed by pairing that information with surveyed data from building use and number of buildings on different categories by Takebayashi *et al* (2015).

High-level category mostly comprise studies that utilize advanced methods for rooftop digitization, insolation calculations, and accounting for aspects and shading of buildings. As an example, Bergamasco and Asinari (2011b) incorporate geographical and cadastral data in GIS, combine with computational algorithms for roof shading, topology, and surface occupied in roofs across Turin, Italy. Hong *et al* (2016) utilize GIS maps for insolation calculations and building suitability assessments, and calculate building shadows for the technical, physical, and geographical rooftop PV potential assessment in the Gangnam district in Seoul, Korea. Another example of a study that falls in this category is that from Hofierka and Kanuk (2009) who develop a GIS-based 3D model of Bardejov, Slovakia, and incorporate digital orthomaps and elevation models to study the city's PV potential. Jakubiec and Reinhart (2013) utilized a suite of GIS data, LiDAR measurements and daylight simulations (Daysim engine) to accurately predict and validate a rooftop PV output both within selected buildings within Cambridge, Massachusetts, and then the city itself. This work ultimately lead to the development of www.mapdwell.com (Mapdwell 2017). In a similar vein, Google has developed Project Sunroof which uses GIS data, 3D modeling derived from aerial



imagery, and shading calculations to predict PV energy generation potential at a rooftop level across hundreds of cities in the United States (Google 2017). These methods can be more computationally intensive (Arnette 2013).

It is important to note that a breadth of literature can be justified as being placed in transition regions in figure 2. An example is the case of Najem (2017) who does not develop high-resolution techniques but rather utilizes them in combination with additional data (e.g. road network topology), and provides a generalized approach to calculate PV rooftop potential.

A selection of studies are excluded from figure 2 chiefly due to their broad regional, province, or national scope (Izquierdo *et al* 2008, Lopez *et al* 2012, Ordóñez *et al* 2010), or their focus on only a segment of building types (Gagnon *et al* 2016, Kurdgelashvili *et al* 2016).

By inspecting the spread of the literature data points across figure 2, methodologies that can cover thousands of cities at medium or high resolution are noticeably lacking.

To determine the deviation between highly generic, widely-applicable rooftop PV assessments and computationally intensive, highly resolved techniques, we compare the highest resolution level techniques in figure 1 with the IEA's methodology defined in the previous section. The IEA Energy Technology Perspectives report (2016) aggregates the most statistical data of any of the methods, and therefore, has been chosen as the baseline low-level approach to determine rooftop PV potential. Figure 3 (a) shows the annual PV electricity potential for 3

select cities or fractions of them: Gangnam district of Seoul, Korea (Hong *et al* 2016), Bardejov, Slovakia (Hofierka and Kanuk 2009), and San Francisco, USA (Mapdwell 2017). Figure 3(b) shows the percent difference, as defined in equation (4), for highly-resolved techniques that were applied to multiple cities. Ko *et al* (2015) considers seven cities in Taiwan; Mapdwell considers ten cities, eight in the USA and two in Chile (Mapdwell 2017); Bergamasco and Asinari (2011b) consider 134 municipalities in Turin, Italy; Google Project Sunroof considers over 40 000 urban census tracts in USA (Google 2017). As can be seen in figure 3, there are large discrepancies in the estimated rooftop PV potential when comparing high-level and low-level approaches, irrespective of the number of cities covered. This suggests that existing generic PV rooftop assessments may be too inaccurate to be widely used for tailored policy designs.

4. Conclusion

Despite the attractiveness of employing a method that could assess rooftop PV potential across thousands of cities, current approaches tend to vary widely when compared with more in-depth approaches over the same geographies. The results presented aim to quantify the variation between different methodologies with varying spatial resolutions across multiple cities. The rooftop PV estimates found using the generic IEA method varied significantly from the highly spatially resolved techniques with an

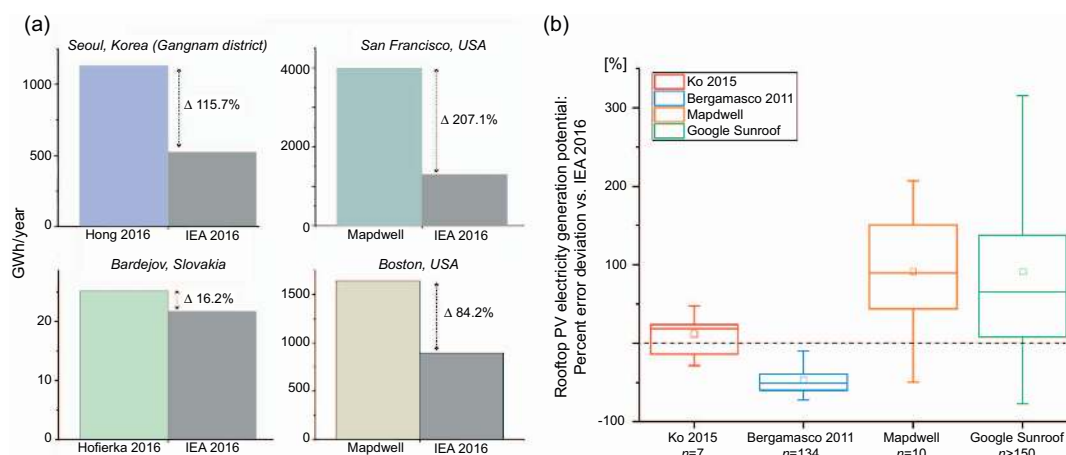


Figure 3. (a) Rooftop PV electricity generation potential (GWh yr^{-1}) comparison between selected high spatial resolution methodologies that focus on individual cities (Hong *et al* (2016), Hofierka and Kanuk 2009, and Mapdwell (2017): San Francisco, USA and Boston, USA) and the low spatial resolution methodology from IEA (2016). (b) Percent error deviation between four different high resolution and low resolution methodologies involving multiple reported cities: Ko *et al* (2015), Bergamasco and Asinari (2011b), Mapdwell (2017), and Google Project Sunroof vs. IEA (2016). Box plots show the 25th, 50th, and 75th percentiles of the data, with cap ends showing the 5th and 95th percentiles to exclude outliers. Mean values are represented as a square, and a dashed line is shown at the 0% error deviation compared to the IEA 2016 methodology. Plotted values are in units of percent, ranging between -78% and 315% .

average absolute percent difference of 110%. It was difficult to compare the highly spatially resolved techniques against each other, as they considered different geographic areas. Furthermore, lack of validation across models or against existing rooftop installation performances tend to increase the uncertainty in the assessments of rooftop PV potential.

Policy makers are often faced with a difficult decision. They either need to rely on generic rooftop PV assessments with potentially low accuracy or to invest in high resolution research in their geographic area of interest. For many decision makers risk aversion would prevent the use of the former and resources may not be available for the latter, which tend to require expensive data collection with difficult calibration and large computational resources. Further research is needed to (i) validate the high resolution, geostatistical approaches, (ii) apply high resolution techniques to more cities, and (iii) extract information from the high resolution models to build a more accurate and robust generic rooftop PV assessment tool applicable to most, if not all, cities.

The authors acknowledge that the body of literature herein presented might have left room for more publications to be included in figure 2, and compared in figures 3(a) and (b). Nevertheless, our aim is to provide a framework to categorize methods to assess rooftop PV potential at the city level and elucidate variations observed amongst high- and low-level approaches.

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ORCID iDs

Sergio Castellanos  <https://orcid.org/0000-0003-3935-6701>

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