Estimating Rooftop Suitability for PV: A Review of Methods, Patents, and Validation Techniques

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National Renewable Energy Laboratory

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Table of Contents

List of Tables

List of Figures

Introduction

A common question throughout solar energy research is: What is the technical potential of solar energy, given the total available land and rooftop area? For researchers looking to understand the market potential of rooftop-installed photovoltaics (PV) in particular, understanding the amount and characteristics of rooftop space that is available for installing PV is essential. Many methods of estimating rooftop area have been developed, ranging from simple multipliers of total building space to methods that employ complex geographic information systems (GIS) or three-dimensional (3-D) models. This report reviews the literature and presents an alternative method for estimating rooftop suitability for PV that was developed by the National Renewable Energy Laboratory (NREL).

This report reviews the literature on rooftop-area estimation to show how others have attempted to capture this difficult measurement. It reviews 35 studies and 6 patents. Many of the studies also estimate potential generation from PV systems; while this report describes those methods, it focuses on the rooftop-area estimation methods.

Table 1 presents the advantages and disadvantages of the three major rooftop-area estimation methods reviewed in the first three sections of this report: constant-value (Section 1.1), manual selection (Section 1.2), and GIS-based methods (Section 1.3).

Table 1. Advantages and Disadvantages of Three Major Rooftop-area Estimation Methods

	Advantages	**Disadvantages**
Constant-value Methods	This method is quick and rooftop area is easy to compute.	Generalized results do not consider localized rooftop characteristics. Results are difficult to validate.
Manual selection methods	These methods are detail-specific and enable assumptions based on specific knowledge of regions and buildings.	Manual selection methods are time-intensive and not easily replicable across multiple regions.
GIS-based methods	These methods are detail-specific and replicable across multiple regions. They can be automated for less hands-on computing.	GIS-based methods are time-intensive and computer-resource intensive.

Table 2 summarizes the wide range of metrics and results for each method found in the literature. These variations suggest that the literature cannot be used alone to validate estimates of rooftop PV availability for specific areas; rather, area- and project-specific validation methods are required. Section 2 summarizes the existing patents for similar methods of determining suitable areas for PV. Section 3 reviews the studies that validate their results. Sections 4 and 5 outline NREL’s estimation method and validation of that method. Section 6 provides a discussion and conclusions.

Table 2. Range of Rooftop PV Availability Found in Reviewed Literature

Method Type	Number of Studies Reviewed	Percent of Total Rooftop Area Suitable for PV	Percent of Total Buildings Suitable for PV	PV-suitable Rooftop area per Capita	Potential Percent of Energy Demand/ Consumption from PV
Constant-value methods	11	15%–65%	N/A	13.4–70 m^2	10%–100%
Manual selection methods	9	1.31%–55%	N/A	N/A	N/A
GIS-based methods	15	6.5%–59%	49%–50%	N/A	5%–45%

1 Literature Review

1.1 Constant-Value Methods

Constant-value methods of estimating rooftop availability are popular due to their ease of use; they are not time- or resource-intensive, and they provides a useful starting point for potential rooftop solar energy generation in a region. Many of the constant-value methods of rooftop-area estimation consider typical rooftop configurations and estimate a multiplier that can be applied to an entire region. Most of these studies make rule-of-thumb assumptions about the proportion of sloped versus flat roofs, the number of buildings with desirable rooftop orientations, and the amount of space obstructed by building components such as heating, ventilation, and air-conditioning (HVAC) systems and shadows. A variation of the constant-value method involves estimating available rooftop space based on the population density of a region. Table 3 summarizes the constant-value findings for studies that include at least some of the metrics found in the literature (see Table 2).

Table 3. Findings of Studies about Constant-value Methods

Study	Study Area	Percent of Total Rooftop Area Suitable for PV	PV-suitable rooftop area per capita	Potential percent of energy demand/ consumption met by rooftop solar
Chaudhari et al. 2004, Denholm and Margolis 2008, Frantzis et al. 2007, Paidipati et al. 2008	United States	60%–65% (commercial) 22%–27% (residential)	—	—
Frantzis et al. 1998	Minneapolis/St. Paul metro area	35%–65% (flat) 16% (pitched)	—	Up to 23% (total demand); up to 50% (daytime peak)
Ladner-Garcia and O'Neill-Carrillo 2009	Puerto Rico	50%	—	All residential energy from 25% of residential rooftop space available; all commercial and industrial energy from all available rooftop space
Vardimon 2011	Israel	30% (all buildings) 50% (large buildings only)	—	32% of electricity consumption (all buildings); 10%–15% (large buildings only)
Eiffert 2003, IEA 2001	23 IEA countries	15% (Japan)–57.8% (United States)	—	—
Lehmann and Peter undated	Northrhine-Westfalia, Germany	—	13.4 m^2 (rooftop) 7.1 m^2 (façade)	—
Wiginton et al. 2010	Southeastern Ontario	30%	70 m^2	30% of electricity demand

A series of reports from Navigant and NREL (Chaudhari et al. 2004, Denholm and Margolis 2008, Frantzis et al. 2007, Paidipati et al. 2008) use floor-space data provided by McGraw-Hill to extrapolate total rooftop area from total floor area. Weather-station data from typical meteorological year (TMY2 or TMY3) stations are also used to estimate solar resource throughout the United States. Major assumptions are made about the mix of the overall building stock, estimating that 8% of all U.S. residential rooftops are flat and that 63% of all commercial rooftops are flat. Commercial rooftop space is reduced to account for shading effects, and residential rooftop space is reduced to account for shading, slope, and orientation. These studies conclude that 60% to 65% of commercial rooftop space and 22% to 27% of residential rooftop space is suitable for PV, depending on whether the climate is warm or cool.

Many other studies also make general assumptions regarding the proportion of pitched and flat roofs and estimate the total available rooftop space based on these building characteristics. Frantzis et al. (1998) identify buildings in the Minneapolis-St. Paul metropolitan area. They assume that 5% of flat-roofed buildings are covered by HVAC equipment or other building components that cause shadowing over 35% of the entire rooftop. They also assume that 30% of pitched roofs have an ideal orientation of 135 to 270 degrees. Applying these constants to the available building stock, determined from the 1990 Census and accounting for assumed shading from trees and building components, they conclude that 35% to 65% of flat roofs and 16% of pitched (residential) roofs are available for PV. They estimate that, with that amount of available rooftop space, up to 23% of total electric sales and up to 50% of daytime peak loads could be generated with rooftop solar power.

Other research uses an even more general estimating approach, applying a constant value to the entire building stock, regardless of slope or orientation. Ladner-Garcia and O'Neill-Carrillo (2009) apply a constant value to total building area to estimate the PV energy potential for Puerto Rico. The total number of buildings is retrieved from the U.S. Census and rooftop area calculated assuming a typical square footage for all residential, commercial, and industrial buildings. Half of all rooftop area is deemed suitable for PV to account for shadows and uncertainty in rooftop layout, and rooftop area is assumed to be distributed throughout Puerto Rico in proportion to the population. Using solar resource data for Puerto Rico, temperature and weather data for Puerto Rico, and PV panel specifications, the researchers estimate that all of the region's residential energy needs could be supplied using 25% of the total residential rooftop space available, and that all of the commercial and industrial energy needs could be supplied with all available commercial and industrial rooftop space.

Vardimon (2011) estimates rooftop area in Israel using building data and shapefiles from the Israeli Central Bureau of Statistics. The buildings are classified by type (commercial, industrial, residential) and size, and a constant value of 30% is applied to the entire building stock as an assumed availability factor for rooftop area. The constant value is determined using considerations from other published studies included in this report as well as discussions with local solar installers. This "Total Potential Scenario" yields an estimated energy production potential equivalent to 32% of Israel's electricity consumption. An alternative "Economic Scenario" is run using only buildings with rooftops that are larger than 800 square meters and have an assumed suitable rooftop area of 50%. Under this scenario, rooftop PV could provide an estimated 10% to 15% of the nation's electricity production.

Another common method of determining a constant value for rooftop-area estimation is based on a region's population density. Such studies apply a generic value to the entire building population to identify rooftop area suitable for PV but use a population-density formula to generate a more geographically specific value.

Reports from NREL (Eiffert 2003) and the International Energy Agency (IEA 2001) estimate rooftop availability for all 23 IEA countries. They evaluate buildings based on architectural and solar suitability. Architectural suitability includes characteristics such as building components (e.g., HVAC, elevators), historical considerations, and shade. Solar irradiation values that account for slope and orientation are considerations for solar suitability. Variables used in the calculation include building area per capita, population size, solar yield, solar irradiation, and global conversion efficiency; a constant utilization factor of 0.4 is applied. Each country is assigned a constant rooftop-availability value based on population density, which factors in each of the other components. Eiffert (2003) and IEA (2001) do not discuss how the utilization factor, a value that describes the suitability of rooftops relative to total ground floor area, is derived. The reports conclude that 57.8% of U.S. rooftop space has suitable architecture and solar exposure for PV. Other countries range from 15% (Japan) to 48% (Spain). These constant values are calculated by sampling a small section of buildings in each country and applying those values to the total building stock.

In a study of the European Union, Lehmann and Peter (undated) use a data set of buildings in Northrhine-Westfalia, Germany, with an assumed 13.4 square meters per capita of rooftop area and 7.1 square meters per capita of façade area suitable for PV. Correlation curves between rooftop area and population density are applied across all European Union countries to estimate potential solar energy generation. A similar analysis for southeastern Ontario (Wiginton et al. 2010) uses building footprints from a sample of 10 census areas to estimate rooftop availability. The building footprints are from Queens University, for neighborhoods with existing GIS data sets, and they are extracted from aerial imagery. Combining the building footprints with census data, the researchers estimate that about 70 square meters per capita of rooftop space are suitable for PV. For the sampled areas, this equates to 30% of the total rooftop area. Applying the constant value of 30% to the rest of the study area—covering 48,000 square kilometers and 1.9 million people in southeastern Ontario—it is estimated PV could generate up to 6,909 gigawatt-hours (GWh) of energy per year and supply about 30% of Ontario's annual electricity demand.

1.2 Manual Selection Methods

Manually selecting rooftops from sources such as aerial photography represents a much more refined—albeit more time-intensive—method of identifying suitable rooftop space than constant-value methods. Table 4 summarizes the findings of studies about manual selection that include at least some of the metrics found in the literature (see Table 2).

Table 4. Findings of Studies about Manual Selection Methods

Study	Study Area	Percent of Total Rooftop Area Suitable for PV	Potential Percent of Energy Demand/Consumption Met by Rooftop Solar
Johnson and Armanino 2004	Marin County, California	—	Up to 30 megawatts (MW) of capacity
Armanino and Johnson undated	Phoenix and Scottsdale, Arizona	1.31%–11.6%	—
Nguyen and Pearce 2012, 2013	Kingston, Ontario	33%	—
Root and Perez 2006	Parking lots in 19 New York counties	—	2,947 MW of capacity
Zhang et al. 2009	Newark, Delaware	—	—
Bright and Burman 2010	Portland, Oregon	3% of total district area (not only rooftop area)	30%
Ordonez et al. 2010	Andalusia, Spain	51%–55% (flat) 16%–21% (pitched)	—

The Community Development Agency in the County of Marin, California, conducted two studies to estimate rooftop suitability; one was in the County of Marin (Johnson and Armanino 2004) and one was in Phoenix and Scottsdale, Arizona (Armanino and Johnson undated). In both studies, rooftops are manually identified from aerial imagery based on their solar resource, land use, and location away from large HVAC units or other objects that could create large shadows. The footprints for these buildings are digitized and their rooftop areas are calculated. The total area is reduced by 25% to account for loss of PV performance due to panel spacing and other potential losses. In the County of Marin study, the analysts conclude that 7.7 million square feet of commercial rooftop area, 1.8 million square feet of institutional facilities rooftop area, and 3.4 million square feet of parking lot area along Highway 101 through the county could be used for PV and could provide up to 30 megawatts (MW) of electricity-generation potential. In the Arizona study, the analysts conclude that rooftop area available for PV ranges from 1.31% to 11.6% of total rooftop area.

Analyses in Vienna, Austria (Wittmann and Bajons 1997), and Kingston, Ontario (Nguyen and Pearce 2012, 2013) use a similar approach. These studies select rooftops from aerial imagery with characteristics that appear suitable for rooftop PV (e.g., flat and south-facing roofs) and which appear to have no significant shade from building components or nearby trees and buildings. The Vienna study classifies buildings by slope, with 0 to 15 degrees being assumed flat and two additional classes with slopes ranging from 15 to 45 degrees and 45 to 75 degrees. Slope data are taken from aerial photography using estimated heights. The classified slope data are combined with local solar resource data from nearby meteorological stations. No results are presented in this study, and the analysts only mention shading criteria as a factor for future study.

The Kingston studies (Nguyen and Pearce 2012, 2013) apply constant values to the selected rooftops, ranging from 50% to 62.5% for pitched roofs and 100% for flat roofs. Factoring in ratios of flat and pitched roofs and the space that is unobstructed by shading as found in the manual building-extraction processes, the researchers estimate that approximately 33% of total rooftop space is available for PV. The 2013 Kingston study goes further by using GIS tools to model sun positions on rooftops. This follow-up analysis is discussed in detail in Section 1.3.

A study specifically targeting parking lot areas in New York State (Root and Perez 2006) also identifies suitable area using aerial imagery. Root and Perez place parking lots in categories ranging from "no obstruction" to "major obstruction" based on the amount of shade covering each lot. The area that is suitable for PV within a parking lot is calculated based on these categories. Counties range in solar energy potential from a 9.6 MW to 552 MW, with a total 2,947 MW of potential for the entire 19-county study region.

Many studies use online tools such as Google Earth and NREL's IMBY (In My Backyard) to select suitable rooftops. For example, analyses of Newark, Delaware (Zhang et al. 2009), and Portland, Oregon (Bright and Burman 2010), use Google Earth to identify suitable rooftops. The Newark analysis selects only roofs with south-, southeast-, and southwest-facing planes. Rooftops are also visually inspected for shading and building obstructions, and buildings with architectural considerations such as historical designations are excluded. Walking surveys in some areas of the study validate the Google Earth selections. Rooftops are digitized from the aerial imagery and sorted according to residential, commercial, industrial, and university designations. The total potential PV generation is calculated using PV Planner software, a program developed by the Center for Energy and Environmental Policy that uses TMY data to simulate PV system performance. The analysis concludes that PV generation could supply over 75% of Newark's daylight-hour energy needs and over 30% of energy needs across all hours.

The Portland analysis (Bright and Burman 2010) considers rooftops, awnings, carports, and parking garages for siting solar water heaters and PV. In this study, suitable areas must encompass more than 100 square feet and have an annual solar access of 97% or greater. The total suitable rooftop area is decreased by 10% to account for unforeseen obstructions. Five regions in Portland are considered. Within each region, a small sample of buildings is measured in Google Earth, and the percentage of suitable rooftop area is applied to the entire region. Measurements are verified in person for a small number of buildings using the sun-eye system, which estimates annual shade coverage. The study concludes that about 3% of total district area—not just rooftop area—is usable area for solar technology.

Google Earth is also used, along with local construction data, in an analysis for Andalusia, Spain (Ordonez et al. 2010). This analysis uses sampling methods and manual rooftop identification to estimate the availability of residential rooftop space for PV. The analysts sample buildings by type, including detached/semi-detached houses, townhouses/row houses, and high-rise buildings. The footprint for each sampled building is manually digitized from Google Earth, and a 3-D model is created in AutoCAD. Using the 3-D model, areas obstructed by HVAC equipment, antennas, chimneys, and other objects are excluded from the total rooftop area. Rooftops are categorized by flat and pitched roofs, and a 1-meter perimeter is assumed necessary around all installations to account for maintenance work. The sampled buildings suggest that 51% to 55% of flat roof surface area and 16% to 21% of pitched roof surface area could be used for PV.

The IMBY[1] web application allows users to view aerial imagery and draw a PV system on any building to calculate potential energy output, costs, and savings. Anderson et al. (2010) use IMBY to estimate the suitable rooftop area for a sample of buildings in New York City, and they apply the resulting percentage to the study area of 10 utility-area networks in the city. The available rooftop space is used in calculations to determine total PV energy potential in the network.

[1] IMBY was integrated into PVWatts in 2013 and is available at pvwattsbeta.nrel.gov

1.3 GIS-based Methods

The majority of rooftop analyses use GIS-based methods for estimating the suitable space for rooftop PV. The key distinction between these methods and the previously discussed methods is that decisions about rooftop suitability are not made using predetermined constant values or by manually selecting buildings. Instead, ideal values for rooftop characteristics are input into a computer model, and the GIS software determines areas of high suitability. This often results in a quicker, more objective, and more accurate method for identifying rooftop availability.

GIS-based methods use primarily 3-D models to determine solar resource or shadow effects on buildings. The 3-D models are most often generated from orthophotography or light detection and ranging (LiDAR) data, and they are combined with slope, orientation, and building structure data to estimate total solar energy generation potential. As LiDAR data has become more widely available at higher resolutions in recent years, this has become a much more desirable method for estimating rooftop area. Table 5 summarizes the findings for GIS-based studies that include at least some of the metrics found in the literature (see Table 2). Table 6 lists the GIS software used in the literature reviewed in this report.

Table 5. Findings of Studies about GIS-based Methods

Study	Study Area	Percent of Total Rooftop Area Suitable for PV	Percent of Total Buildings Suitable for PV	Potential Percent of Energy Demand/Consumption Met by Rooftop Solar
Jofierka and Kanuk 2009	Bardejov, Slovakia	35% (residential) 59% (total)	—	45%
Compagnon 2004	Fribourg, Switzerland	6.5%–21%	—	—
Kodysh and Omitaomu undated	University of Toledo, Ohio	—	—	5%
Anders and Bialek undated	San Diego County, California	12.6% of total developed land	50%	—
Santos et al. 2011	Lisbon, Portugal	—	49%	—

Table 6. GIS Software Used in Reviewed Literature

Content	Website
ArcGIS Spatial Analyst (Hillshade and Area Solar Radiation tools)	www.esri.com/software/arcgis/extensions/spatialanalyst
Autodesk Ecotect	usa.autodesk.com/ecotect-analysis
Google Earth	www.google.com/earth
Google SketchUp	sketchup.com
GRASS r.sun	grass.osgeo.org/grass64/manuals/r.sun.html
PVGIS	re.jrc.ec.europa.eu/pvgis
RADIANCE/DAYSIM	daysim.ning.com

Studies in Bardejov, Slovakia (Jofierka and Kanuk 2009), and Chandler, Arizona (Jo and Otanicar 2011), use orthophotography to create a 3-D model and estimate solar resource. The Bardejov study processes the 3-D building model in r.sun, a GRASS solar radiation tool similar to the ArcGIS Hillshade tool, to create a solar radiation map of the city. The r.sun tool returns the estimated areas of shadow and strength of solar radiation. The solar radiation map is used in coordination with PVGIS, a program designed specifically for Europe and Africa to estimate energy potential from a 1-kilowatt-peak system using GIS data, to estimate the total potential energy output from PV. The study concludes that 25 GWh of PV electricity could be produced annually, which is 45% of the current electricity consumption of the region. The study also concludes that approximately 35% of residential rooftop space and 59% of total rooftop space could be used for PV systems.

The Chandler study (Jo and Otanicar 2011) assesses imagery for brightness value to determine the potential areas of shadow and obstructions on commercial and government rooftops in a 4-square mile area of the city. The lengths of shadows are estimated in detail using Google SketchUp by casting simulated shadows on a 3-D building model. The obstructions identified during the satellite imagery processing are buffered by a distance equal to the shadow lengths estimated in SketchUp. These areas are subtracted from the total rooftop area to estimate the area suitable for PV. The researchers visited 150 of the 932 buildings included in the study to take ground-truth measurements and validate the accuracy of their model.

In the follow-up analysis to the original Kingston, Ontario, study (Nguyen and Pearce 2012) mentioned in Section 1.2, analysts ran a sample of 100 buildings through the GRASS r.sun tool (Nguyen and Pearce 2013). Rooftops with a southeast- through southwest-facing aspect (90 to 270 degrees) and a slope within 15 degrees of the local latitude are considered suitable for PV. The results are validated on one rooftop in Kingston, where the shadows were measured during a morning hour and an evening hour to compare to the modeled results.

RADIANCE/DAYSIM, a program designed to simulate lighting scenarios, is used in an analysis in Fribourg, Switzerland (Compagnon 2004), and an analysis for Cambridge, Massachusetts, conducted by the Massachusetts Institute of Technology (MIT; Jakubiec and Reinhart 2013). The Fribourg analysis uses a 3-D building model for 61 buildings in the study area. The methods for developing the 3-D building model are not discussed. The building model is run through

RADIANCE/DAYSIM, and researchers place a minimum of 1,000 kilowatt-hours per square meter (kWh/m^2) on the model to determine suitable rooftop areas. The study concludes that the potential for PV systems ranges from 6.5% to 21% of total roof area. The researchers identify the need for validating the results of the study, which is not included in the scope of this project. The Cambridge analysis also uses the RADIANCE/DAYSIM model to create hourly irradiance maps for the city using the industry-standard Perez all-weather sky model in conjunction with TMY3 data from Boston Logan International Airport. Rooftop area is considered to be suitable for PV if it has a slope less than or equal to 60 degrees and a solar resource value of at least 609 kWh/m^2. Results of this analysis are presented on a building-specific level and are accessible through an interactive Web interface.

Studies in Vancouver, British Columbia (Tooke et al. 2011), and Toledo, Ohio (Kodysh and Omitaomu undated) use the ArcGIS Solar Analyst tool to model the solar resource available on rooftops. LiDAR data are used in the Vancouver analysis to extract building footprints and trees. The solar radiation is estimated using Solar Analyst along with regional weather data obtained from the University of Oregon. The study concludes that solar radiation on rooftops varies from hourly and seasonally, and that trees reduce solar radiation on rooftops by an average of 38%. No additional rooftop analysis is included in this analysis. In the Toledo study, students worked with researchers at Oak Ridge National Laboratory to present a method for estimating the potential for solar energy production on the University of Toledo campus. LiDAR data for the University of Toledo campus is processed to a 1-meter-resolution digital surface model (DSM). The DSM is run through Solar Analyst to produce a solar insolation map. The values from the solar insolation map are aggregated to conclude that 13,400,000 kWh could be produced annually on the campus, generating 5% of its total energy needs.

Another study to use the proportion of flat roofs versus pitched roofs is an analysis for San Diego (Anders and Bialek undated). In this analysis, buildings data from the City of San Diego are used to digitize all building footprints greater than 3,000 square feet. These buildings are run through ArcGIS Solar Analyst to determine the total solar resource available for large-area buildings. Rooftop area is manually assigned to one of three classifications: 20% suitable area, 60% suitable area, or 80% suitable area. The proportions of each class are extrapolated to all commercial buildings in the County of San Diego. It is assumed that 50% of all residential buildings would have space available for PV. Once total rooftop area is estimated, the area is reduced by 20% to account for shading. Using these constant values, it is estimated that 12.6% of total developed land (as opposed to total buildings) is suitable rooftop space for PV in the County of San Diego.

A study of Lisbon, Portugal (Santos et al. 2011), uses LiDAR data to create a DSM that is then used as an input in the ArcGIS Area Solar Radiation tool to create a solar surface map. A solar radiation map is created for each month of the year, and the 12 values for each pixel are averaged to determine a final solar radiation value. Rooftop areas are considered suitable for PV if at least 10 contiguous square meters have more than 1.68 megawatt-hours per square meter (MWh/m^2) of solar radiation and have a slope of less than 45 degrees. The researchers determine that 49% of buildings in the approximately 6-square-kilometer study area in Lisbon have rooftops suitable for PV.

LiDAR data are used in a rooftop analysis of Toledo, Ohio, to model solar irradiation and shadows on roofs (Chanikarn and Mojtaba 2010). Calculations are performed on the LiDAR data to estimate building and tree height by subtracting the first return layer from the bare earth layer. Satellite imagery is also used to verify the locations of buildings and trees. Using Autodesk Ecotect 5.6, a building design software used to analyze and simulate building energy performance, the researchers estimate shadows on rooftops from building components and trees. This analysis provides no specific results or assumptions about what threshold of shadows or rooftop size are considered usable space for PV.

Many studies use LiDAR point data to model solar resource, slope, and aspect in order to estimate suitable rooftop area and potential energy generation. Latif et al. (2012) use LiDAR data to create a DSM for Georgetown, Malaysia. From this DSM, slope, aspect, and solar radiation are calculated. The thresholds for slope include one scenario with a 15-degree maximum slope and a second scenario with a 30-degree maximum slope. Only rooftops with south-, southwest-, or southeast-facing aspects are considered. Additionally, rooftops identified as suitable for PV are required to have at least 1,000 watts per square meter and be at least 2.6 square meters in size, accounting for a 1.5 square meter PV panel size as well as 15% buffer space for the mounting frame and panel spacing. All criteria are converted to a binary value of 1 or 0 to determine suitability. The final step in the analysis, called the "human mask" layer, includes a visual inspection of all potentially suitable rooftops in Google Earth, and a manual decision to include the rooftop in the analysis is made based on the aerial imagery. Validation of the computer model and visual inspection is very limited, including only three buildings inspected in person to validate measurements.

In an analysis of Lujazui, Shanghai, China (Huang et al. 2012), LiDAR points are used to extract building footprints and create a solar radiation layer of the region. Individual roof planes are identified for each building through a manual process using Google Earth. For each roof plane, a single point is identified and assigned a slope and aspect value. Each point is run through a neighborhood analysis in GIS to confirm that all points within a single plane are of the same slope and aspect. Only rooftop planes that are larger than 5 square meters and have a slope of less than 35 degrees; a south-, southwest-, or southeast-facing aspect; and at least 5 megajoules per square meter of solar radiation per day are considered suitable rooftops. The slope, aspect, area, and solar radiation attributes are summed, and the results are collected in a final list of suitable rooftops, although no results are presented in Huang et al. (2012).

LiDAR data are used in a detailed rooftop analysis of a 1-square-kilometer area of Maribor, Slovenia (Lukac et al. 2013), to create a digital elevation model (DEM) and a solar radiance map as well as to calculate the slope and aspect of each roof plane. Additionally, lower-resolution DEMs are used to identify areas of shadow cast by larger regional influences such as nearby hills or mountains. Roof planes are identified using a seed process to group similar cells based on a neighbor analysis. The thresholds for slope and aspect suitability are not discussed. Additional filters considering the cultural or protected status of buildings and the presence of rooftop components such as HVAC equipment and chimneys are also applied, but Lukac et al. do not specify whether this step is done manually or in a GIS. The result of this analysis is a data set of five rankings for PV, ranging from most suitable to unsuitable.

Two California-based analyses (Levinson et al. 2008, 2009) gauge the impact of tree growth over time on rooftops by evaluating residential, tree-dense sample areas in Sacramento, San Jose, Los Angeles, and San Diego in which homes were built in the 1980s; each sample area covers 2 to 4 square kilometers. The ArcGIS Hillshade tool is used on LiDAR data to estimate areas of shadow on rooftops for each hour of the 21st day of each month, resulting in 143 shade simulations per year. If the area of the rooftop is in shadow, it is given a value of 1. The researchers conclude that, over the course of approximately 30 years, rooftop space free from shadows decreased by 50% to 70% due to tree growth. This issue has substantial impacts on rooftop availability estimates in newer neighborhoods, and we have identified it as an area for future research in connection with NREL's work. Levinson et al. (2009) focuses on San Jose and is a more in-depth explanation of Levinson et al. (2008). Using the ArcGIS Hillshade tool, shadows are estimated for a sample area of San Jose for every hour of the 21st day of every month. Areas in shadows are assigned a value of 1, and aggregate values are analyzed to assess the reduction in solar access for residential rooftops that face south, southwest, or southeast. Solar access is reduced 13% to 16% by building components and trees within their own parcel and less than 2% by buildings and trees from nearby parcels.

Additional studies use a variety of the previously discussed methods to estimate rooftop space available for PV. Liddell (2010) presents a method for estimating suitable rooftop space using shading, slope, aspect, and size as inputs. This study focuses exclusively on the Seattle, Washington, area and does not provide any details about how the three criteria are used to determine rooftop space. No results had been presented as of 2010, the date of Liddell's presentation. Kodysh et al. (2013) use LiDAR data to calculate slope, aspect, and solar radiation values—determined by cloud cover and transmissivity data—for Knox County, Tennessee. Building footprints are extracted from a DEM and buffered by 25 meters to lessen the amount of data needing processing while still capturing shading influences from nearby buildings and trees. Results from the analysis are on a building-specific level, and no aggregate results are presented.

2 Patent Search

In addition to the studies summarized above, we conducted a detailed patent search and identified six U.S. patents that are relevant to rooftop-area estimation methods for PV. Table 7 summarizes the patent information found.

Table 7. Results of Patent Search

Patent	Data Source	Product	Notes
University of Hawaii (Meder et al. 2007)	Aerial photos, DEMs, walking and driving surveys	Assessment of solar insolation values for various rooftop types	Study area is Mapunapuna district, Hawaii
Ecometrics, LLC (Woro 2009)	DEM from LiDAR data or aerial photos	Tabular results of solar insolation values on a building-specific level	Shadow simulations run against building data at 6-minute intervals
Ecometrics, LLC (Woro 2010)	DEM from LiDAR data or aerial photos	Tabular results of solar insolation values on a building-specific level	Adds solar irradiance component to Woro (2009) patent
CH2M Hill (Hochart et al. 2009, Palizzi 2008)	LiDAR data, stereo photos, aerial photos, construction data, survey and measurement data	Method for estimating usable rooftop space for solar; resulting data incorporated in online mapping tool	Does not incorporate slope or aspect data in calculations
Geostellar (Levine et al. 2011)	LiDAR, stereo imagery, and color infrared imagery	Quantifies the levelized cost of energy (LCOE) based on shadow, slope and orientation of facets, as well as economic suitability based on tariffs, load, and incentives	Available through Web and iOS app, integrated with social networks
Augenbraun et al. (2012)	Aerial photos	Method for estimating “power flux” to create an executable software package and mobile application	Unique feature is using shadows to identify obstructions

A 2007 patent for the University of Hawaii (Meder et al. 2007) uses aerial photographs and DEMs to identify rooftop areas within the study area of the Mapunapuna district in Hawaii. Researchers identified six sample neighborhoods and conducted walking and driving surveys to take measurements and verify rooftop characteristics identified in the aerial photography. Each rooftop is classified into a specific architectural type, such as gable, hip, or shed. For each rooftop type in the sample areas, the slope, horizontal global insolation, and rooftop orientation are calculated. ArcGIS Solar Analyst is used to estimate solar radiation values for the average day of the average year. The final product produced is an assessment of solar insolation values for various rooftop types in the sample areas.

A 2009 patent for Ecometrics, LLC (Woro 2009) provides a detailed method for estimating the solar potential of rooftops. Building footprints are extracted from a DEM derived from either LiDAR data or aerial photography. Shadow simulations are run against the building data at 6-minute intervals by triangulating the sun angle against the building data; they are then aggregated to identify the ideal rooftop areas for PV. The results are combined with size, slope, and orientation data to provide tabular results of solar insolation values on a building-specific level.

A second patent for Ecometrics, LLC (Woro 2010) builds on the first to include a solar irradiance component. The 6-minute shadow simulations are reclassified to create a normalized shade file for each interval. Each interval file is summed to create an irradiance-weighted shade file. The irradiance-weighted shade file is divided by the time frequency interval to determine a solar access value for each rooftop area. The solar access values are used in combination with slope, orientation, and rooftop material to identify suitable areas for PV construction.

The CH2M Hill online solar mapping program, S.A.F.E., is included in their 2009 patent (Hochart et al. 2009, Palizzi 2008) to develop a method for estimating usable rooftop space for solar installation. The resulting data are incorporated in an online mapping tool. Rooftop data are obtained from a variety of sources, including LiDAR data, stereo photography, aerial photography, construction data, and survey and measurement data. A time-series shading analysis is performed for multiple sun angles and the resulting data are aggregated to determine whether a particular roof area meets an undisclosed threshold for solar suitability. The solar energy potential is calculated from the total rooftop area meeting that threshold. Areas determined to be suitable for rooftop solar installation are loaded into an interactive mapping platform and made available to the public. Users of S.A.F.E can query specific buildings to learn about potential energy production, savings potential, carbon dioxide reduction, and return on investment.

Geostellar’s 2011 patent (Levine et al. 2011) performs a suitability analysis for a variety of renewable energy technologies on a regional scale, with an emphasis on solar. Specific to the solar component of this patent, the researchers use DSMs to determine the amount of time that a 1-square-meter pixel is in sunlight, both on a monthly timeframe and a daily timeframe. The number of minutes a region is in sunlight is divided by the total number of minutes of daylight to calculate solar availability. The results for each month are summed to calculate an average solar availability for the year. These data, combined with rooftop and ground slope, azimuth, buildable area, utility rates, incentives, and load data, are applied to a parcel data layer to determine the specific costs and benefits of various solar equipment and financing options for each parcel of land.

In a 2012 private-party patent (Augenbraun et al. 2012), researchers identify a method of estimating “power flux”—a measure of light energy—to create an executable software package and mobile application. In this method, the individual roof planes are identified manually and their orientation recorded. These roof planes are used to create a 3-D building model. Aerial photographs are used to identify shadows cast within the study area, and the shadows are used to identify likely obstructions. This method of using known shadows to locate obstructions is a major difference between this analysis and the majority of other studies, which use known obstructions to estimate likely shadow patterns. Using the obstructions generated from photography, ray traces are run against the 3-D model to create a full shadow map and calculate the power flux. “Keep-out regions” are manually defined and are determined by local requirements and legal restrictions, solar technology limitations, and potential economic payback. The final areas of rooftop solar suitability are loaded into an executable software program and mobile application and made available to external users.

3 Validation of Results

Using results from the literature is challenging because few studies include a process for validating the particular rooftop-area estimation method. Thus, researchers have little information about the accuracy of estimates from most studies. Of the 35 studies included in this review, only seven mention significant efforts to validate results. The validation methods of those that compare results with other sources vary widely in scale and type. Some studies validate against other computer models, some against existing solar resource data, and others by physically inspecting actual buildings. Table 8 summarizes the validation methods used as well as their advantages and disadvantages.

Table 8. Advantages and Disadvantages of Validation Methods Used in Reviewed Literature

Method	No.	Advantages	Disadvantages
Compare to existing computer files or models	2	High availability of resources Low cost Not time consuming	Inability to know accuracy of indirect sources
Compare to installed systems	2	High-quality data to compare against	Low availability of resources Compares to installed infrastructure with economic constraints, not total potential infrastructure based strictly on rooftop characteristics
Physical/on-site inspections	4	High-quality data to compare against	Can be expensive Time consuming Need equipment and permission to take measurements

The analysis of southeastern Ontario (Wiginton et al. 2010) covers an area of 48,000 square kilometers and a population of 1.9 million. Much of the study area did not have readily available building footprint data, so the analysts use Feature Analyst to extract building footprints from aerial imagery. The Feature Analyst results are compared with areas that did have existing building footprint shapefiles, and an error of 15% is found in extracting buildings. However, when accounting for positive and negative errors, the total difference is 2%. No additional validation process is conducted in this study for the actual rooftop suitability measurements.

The MIT analysis of Cambridge, Massachusetts (Jakubiec and Reinhart 2013), reviews several online solar-potential maps. These online maps use many of the same methods included in this review, including using constant-value methods and GIS tools such as Solar Analyst. Jakubiec and Reinhart compare their results with the results of a Solar Analyst method, flat-roof-assumption method, and constant-value method. Accounting for climate data, solar resource, and building component data as well as verifying against two existing PV systems, they find that Solar Analyst slightly underestimates the amount of energy potential, while the flat-roof assumption and constant-value methods greatly overestimate the energy potential. They conclude that their detailed method of rooftop availability more accurately estimates suitable rooftop space than any of the other methods researched.

Most studies that discuss validation compare their rooftop measurement results with those of actual buildings. In some cases—such as in the Kingston, Ontario (Nguyen and Pearce 2012), and Georgetown, Malaysia (Latif et al. 2012), studies—very few buildings are verified. Researchers in the Kingston study measure shadows at one building during both a morning hour and an afternoon hour to validate their results on the study area of 100 buildings. Georgetown researchers identify three buildings in their study area with either existing or planned PV to compare their modeled energy generation. The Newark, Delaware, study (Zhang et al. 2009) includes walking surveys to verify areas with significant shading and rooftop obstructions with results from digitizing rooftop area from aerial photography.

The Portland analysis (Bright and Burman 2010) includes site visits to many of the buildings in the study area with questionable availability of rooftop area. These site visits include actual rooftop measurements as well as analysis of the annual shading effects on the roof using a sun-eye system. The researchers do not discuss how many rooftops are ground-truthed for accuracy. The Chandler, Arizona, study (Jo and Otanicar 2011) includes a visual ground inspection of 150 of the 932 analyzed buildings to validate rooftop obstructions and area estimates with the satellite imagery used in the analysis.

Validation using data from actual buildings is a large component of NREL's effort to develop an improved method (as discussed in Section 5).

4 NREL Method

The literature contains a wide variety of assumptions related to determining ideal rooftop space for PV. Based on the literature review, as well as personal communications with solar technology analysts and installers, NREL determined a core set of guidelines, the "NREL method," that are intended to replicate industry best practices (Table 9).

In contrast to much of the literature reviewed in this report, the NREL method does not make assumptions about ideal rooftop characteristics other than the broad specifications outlined in Table 9. This analysis aims to provide information about the variety of rooftop space available and allow users of the data to extract the total amount of ideal rooftop space available for PV depending on their particular research questions. Providing the data in this manner allows for a greater range of research with various PV technologies as well as the ability to adapt research with this data set as PV technology continues to become more efficient.

Table 9. Assumptions in Reviewed Literature and NREL Method

	Range of Assumptions from Reviewed Literature	NREL Assumptions
Slope	Maximums vary from 0 (flat roofs only) to 45–75 degrees; others define ideal slope as equal to or within 15 degrees of local latitude	Maximum of 60 degrees
Orientation	Varies from south-facing only to ranges within east–south–west	Range from east–south–west
Shade	Extreme variation in definitions and methodologies for estimating shade	Rooftop in sunlight for the minimum number of hours required for 80% generation, estimated regionally
Size	Varies from no size requirements to minimum contiguous areas of 9 to 100 m^2	Minimum of 10 contiguous m^2

Figure 1 outlines NREL's method. It uses 1-meter resolution LiDAR data and building footprint data provided by the U.S. Department of Homeland Security (DHS).[2] It uses ArcGIS tools to model slope, orientation, and shading characteristics of roof panels. The NREL method produces a data set listing roof panels with a slope less than 60 degrees, an orientation ranging anywhere from east to west, the number of hours per day in sunlight averaged annually, and size.

[2] DHS has made data available to government agencies for more than 120 U.S. cities.

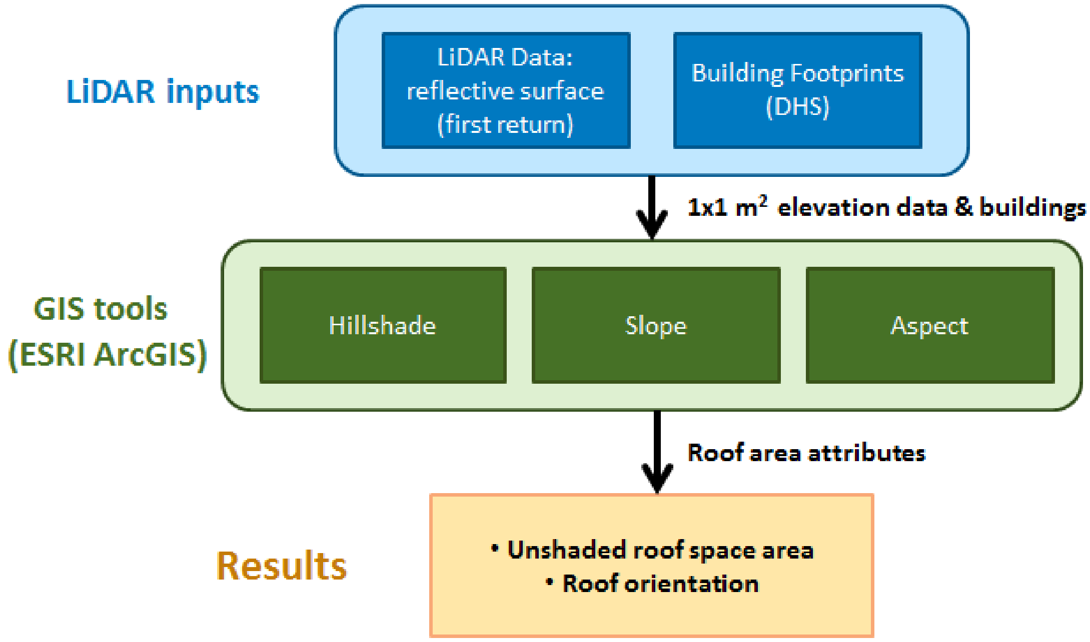

Figure 1. NREL method for processing LiDAR data

The shading component of the NREL method is calculated by running the Hillshade tool in ArcGIS for every daylight hour on March 21, June 21, September 21, and December 21. The shade files are reclassified into a binary value to determine which hours of the day the roof panel is in sunlight. All hours for individual months are added together to determine a daily sunlight availability, and then the four months are added together and divided by four to estimate the annual average sunlight availability.

The number of hours a rooftop should be in sunlight to produce a minimum threshold of energy is determined on a city-by-city basis using NREL's System Advisor Model (SAM).[3] SAM estimates the total number of daylight hours a rooftop in a specific region would need to be in sunlight to produce 80% generation, a best-practice threshold derived from conversations with solar installers and research analysts. Using this value for identifying the minimum threshold for sunlight hours allows the rooftop model to create more region-specific results regarding sunlight criteria.

The slope and orientation components are calculated with the ArcGIS Slope and Aspect tools. To account for edge error, all grid cells with a slope greater than 60 degrees are eliminated from the data set. The roof planes are extracted from the aspect file by selecting all grid cells with the same orientation, and the slope is determined for each roof plane by calculating a zonal average of the slope grid cells within each plane. Areas of at least 10 square meters that meet NREL's assumptions for slope, orientation, and sunlight requirements are considered suitable for PV.

The final data set presents an aggregated value of the total amount of rooftop space available for PV as well as the total number of buildings with at least some portion of rooftop space available.

[3] For more information, see sam.nrel.gov.

The data are intended to be used in the aggregate form to aid in subsequent regional analyses. Additionally, the original generated hillshade, slope, and aspect files are maintained so that analysis involving varying thresholds of suitability can be revisited.

NREL conducted a thorough literature review to identify how others have identified rooftop space suitable for PV and to develop a set of best practices for this type of analysis. The NREL method is very similar, therefore, to much of the previously discussed research. However, a significant difference between the NREL method and many of the methods described in the literature is that the NREL method focuses exclusively on the physical characteristics of the rooftop. Weather and climate data are not included, and the energy potential is not calculated. This allows other analysts to use a comprehensive data set of rooftops and maintain the ability to customize their research based on varying PV technologies.

The NREL method also emphasizes a technique that is replicable on a national scale[4]. Many other studies employ techniques that are more detailed than the NREL method in how sunlight and shade obstructions are identified. The level of detail in these studies provides a strong prediction of sunlight availability on rooftops but makes it difficult to estimate rooftop availability estimates throughout the country due to the large amounts of data and intensive computer processing requirements.

[4] Currently DHS LiDAR data is available for 120 urban and suburban areas in the U.S. Data from these cities will be used to extrapolate rooftop characteristics to other metropolitan areas throughout the nation.

5 Validation of NREL Method

Validation of results obtained using the NREL method is a key component of our analysis. To accomplish this, solar installation data were obtained from Trinity Solar in New Jersey, Namaste Solar in Colorado, and the California Public Utilities Commission in California. Overall, 205 PV arrays across the three states were used to validate the results of this analysis. We evaluated 118 arrays in the Newark and Trenton metropolitan regions, 43 arrays in the Denver/Boulder metropolitan region, and 44 arrays in the Anaheim metropolitan region (Figure 2).

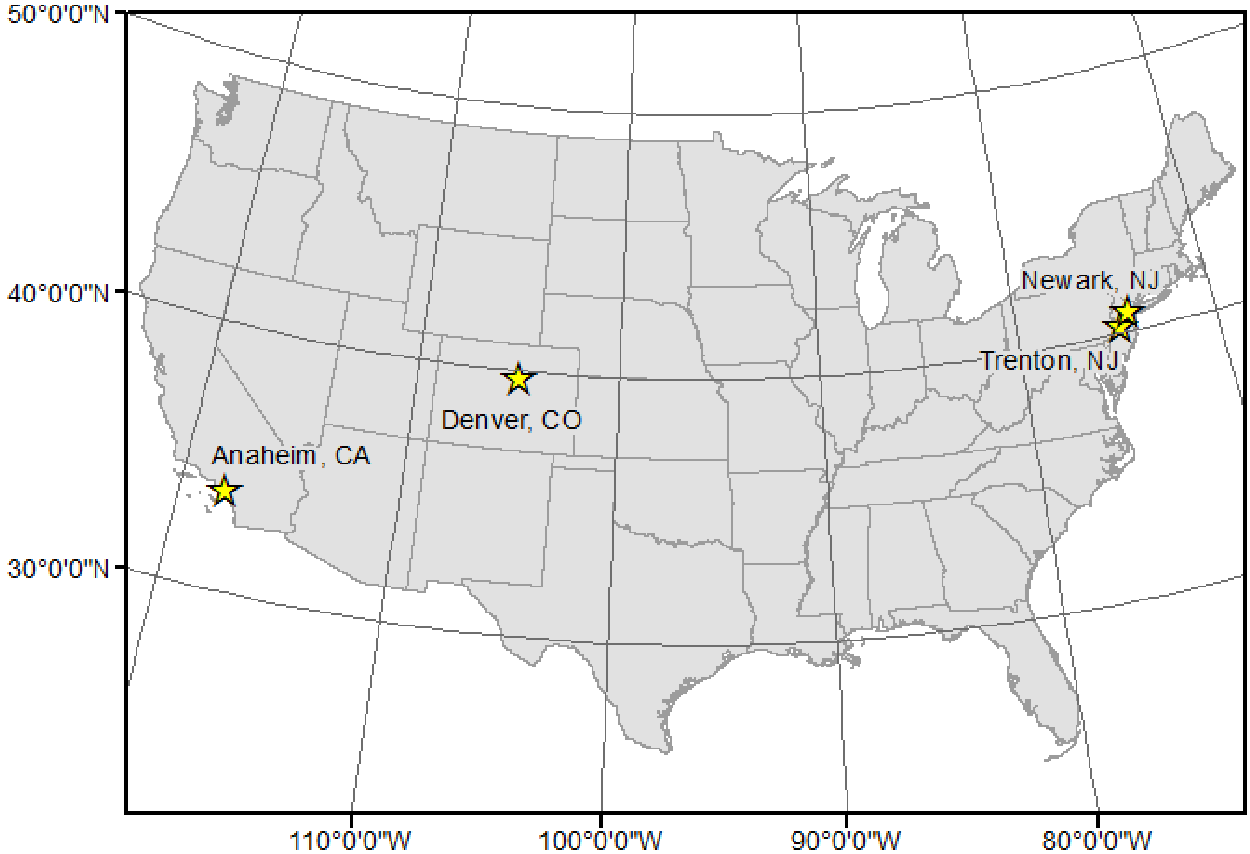

Figure 2. Cities included in NREL validation

Trinity Solar provided the most comprehensive data set in the form of as-built drawings detailing the location of installed panels, their orientation and slope, and the minimum number of hours the panels were estimated to be in sunlight based on initial Solar Pathfinder measurements. Because of the exceptional detail of data provided by Trinity, half of the New Jersey data set was used to calibrate the model initially, and the full data set was then used to validate the results.

The calibration step of the validation process was intended to ensure that (1) model thresholds were appropriately set to capture the rooftops that a solar installer deemed appropriate for PV and (2) unsuitable rooftops were excluded. This step was included specifically for use in determining the number of hours a roof is in sunlight. The ArcGIS Hillshade tool returns a value of 0 to 254, which is directly correlated to the percentage of illumination each grid cell receives.

Through the calibration process, it was determined that grid cells with a minimum value of 50% to 70% illumination were considered to be in sunlight depending on the month, while illumination values lower than those thresholds were considered to be in shade.

Of the 118 PV arrays evaluated in the Trinity data set, 26 required that trees be cut to install panels. Of the remaining 92 arrays, 65% showed modeled results within 5 degrees of Trinity's slope measurements, and 89% of the modeled results were within 10 degrees. Only 10 arrays in the validation data set showed a modeled slope that was more than 10 degrees different from the Trinity measurements. The average difference in slope between Trinity's measurements and the modeled results was 4.4 degrees. Only 2 of the 92 arrays modeled an orientation direction different than the Trinity measurements.

Additionally, 22 of the 26 arrays that required trees be cut showed the results to be incompatible with PV either based on erroneous slope or sunlight estimates, or simply because they did not provide the minimum required area. The error in slope estimates for these arrays is due to the inability of the first-return LiDAR data to estimate accurately the elevation changes in the roof due to obstructions by trees or other shade-casting elements. The negative validation of these 22 arrays verifies that the NREL method will in fact exclude areas with high obstruction.

Four of the arrays identified for tree cutting by Trinity installers did not model significant shading impedance. Two of the roofs showed partial shading in the model, but results showed an acceptable amount of unshaded area for installation. One customer did not take Trinity's recommendation for tree trimming—because the tree belongs to a neighbor—and installed a panel on only the portion of the roof left unshaded by the tree. A third array that did not show shading constraints in the model was one of three arrays installed on that particular roof. The other two arrays did show shading constraints, while the third was installed in an area of the roof not originally affected by tree shading.

As noted in the literature review, tree-shading changes over time and will add unavoidable error in the model. The LiDAR data for New Jersey were collected in 2007 and 2008, while most installation assessments performed by Trinity were conducted in 2011 and 2012. Additionally, the time of year when the LiDAR data were collected impacts the results of the shading analysis. DHS reported that many cities in their data set collected LiDAR data in the spring when trees had full foliage, but the exact timing of the data collection for all cities is unknown.

There were 43 arrays used for verification in Colorado. Because documents for these buildings provide only an address, the capacity of the system (kW), and incomplete data for the measured slope, the exact location of the array and orientation could not be verified. One of these buildings was used for negative validation, having had a solar installer deny PV for that residence based on the amount of tree shading it received. That house also had too few sun hours in the NREL method to be a desirable location for PV. Of the 33 arrays with slope data in the Colorado data set, 70% had a modeled slope within 5 degrees of the measured slope, and 94% had a modeled slope within 10 degrees. The average difference between the measured data and modeled data was 3.6 degrees.

The data set from the California Public Utilities Commission contains data on the capacity of each system (kW) and its location, as well as the slope and orientation of the PV array. This data set was more difficult to validate against because the slope data refer to the tilt of the array, not necessarily the slope of the roof. Of the 44 arrays used in the validation, 8 were flat-roof buildings with tilted arrays. 75% of the buildings had modeled slopes that were more than 5 degrees different from the measured slope, and 86% of the buildings were within 10 degrees. The arrays had an average slope difference of 4.9 degrees. All of the arrays matched between the measured and modeled orientation.

The New Jersey and California data sets provide the panel manufacturer, model, and number of panels installed on the building. These values were used to calculate the actual area required for PV. Using these dimensions, 65% of the model results in New Jersey met the minimum size requirements for the installed panels, and 98% of the California model results met the minimum size requirements. The Colorado data set did not provide panel models or specifications, so assumptions about the footprint size of the array had to be made. Each building in the data set was validated assuming a standard efficiency of 15% and a panel size of 1.63 square meters. Assuming standard efficiency, 79% of modeled results provided at least the minimum amount of area required for the actual installed panels.

The results of the validation process show 89% of the modeled results were within 10 degrees of the actual slope (Figure 3), 96% of modeled results showed the same orientation as the actual orientation, and 99% of modeled results had the required minimum number of sun hours for PV to produce 80% generation (Table 10). All arrays used in the validation process showed at least a portion of the rooftop was suitable for PV, and 79% showed an area at least the size of the actual installed system (Figure 4).

Table 10. Results of NREL Validation

	New Jersey	Colorado	California	Total
Total systems tested for positive validations				
Slope	*n = 92*	*n = 33*	*n = 44*	*n = 169*
Model within 0-5 degrees	60 (65%)	23 (70%)	33 (75%)	116 (69%)
Model within 5-10 degrees	22 (24%)	8 (24%)	5 (11%)	35 (21%)
Model within 10-15 degrees	8 (9%)	1 (3%)	3 (7%)	12 (7%)
Model within 15-20 degrees	0 (0%)	1 (3%)	2 (5%)	3 (2%)
Model within 20-25 degrees	1 (1%)	0 (0%)	0 (0%)	1 (1%)
Model > 25 degrees different	1 (1%)	0 (0%)	1 (2%)	2 (1%)
Orientation	*n = 92*	*n = 0*	*n = 44*	*n = 136*
Model within same orientation	90 (98%)	N/A	44 (100%)	134 (99%)
Model outside orientation	2 (2%)	N/A	0 (0%)	2 (1%)
Sun hours	*n = 92*	*n = 42*	*n = 44*	*n = 178*
Hours modeled sufficient for PV	92 (100%)	40 (95%)	44 (100%)	176 (99%)
Hours modeled not sufficient for PV	0 (0%)	2 (5%)	0 (0%)	2 (1%)
Size	*n = 79*	*n = 42*	*n = 44*	*n = 165*
Modeled results show suitable area	51 (65%)	33 (79%)	42 (95%)	126 (76%)
Model within 0-10% of actual size	10 (13%)	3 (7%)	1 (2%)	14 (8%)
Model within 10-20% of actual size	6 (8%)	0 (0%)	1 (2%)	7 (4%)
Model within 20-30% of actual size	6 (8%)	0 (0%)	0 (0%)	6 (4%)
Model within 30-40% of actual size	2 (3%)	4 (10%)	0 (0%)	6 (4%)
Model within 40-50% of actual size	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Model within 50-60% of actual size	1 (1%)	0 (0%)	0 (0%)	1 (1%)
Model within 60-70% of actual size	1 (1%)	0 (0%)	0 (0%)	1 (1%)
Model within 70-80% of actual size	2 (3%)	0 (0%)	0 (0%)	2 (1%)
Model within 80-90% of actual size	0 (0%)	1 (2%)	0 (0%)	1 (1%)
Model within 90-100% of actual size	0 (0%)	1 (2%)	0 (0%)	1 (1%)
Total systems tested for negative validations				
Tree shading	*n = 26*	*n = 1*	*n = 0*	*n = 27*
Modeled results show shading on roof	22 (85%)	1 (100%)	N/A	23 (85%)

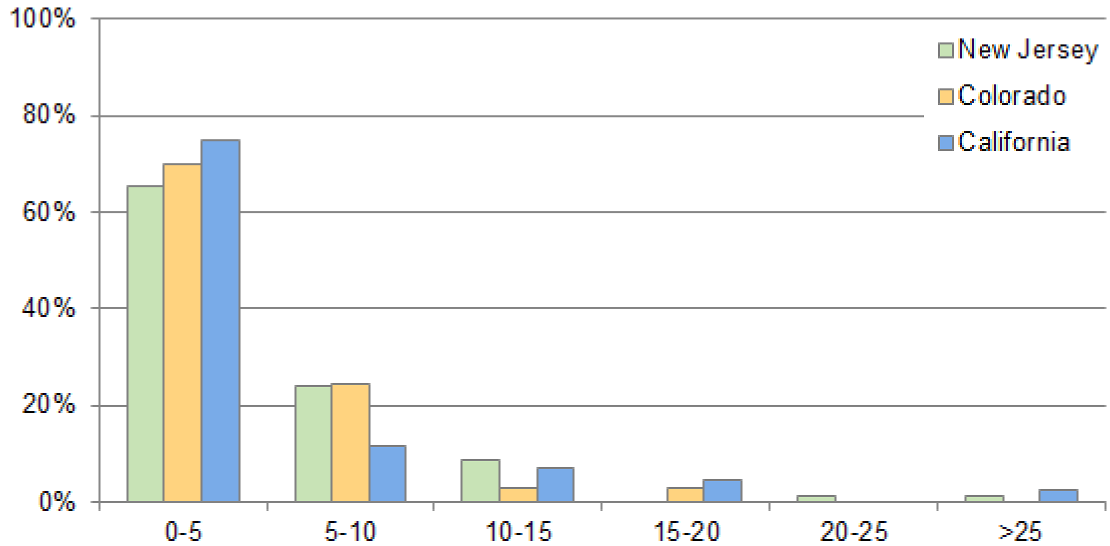

Figure 3. Distribution of difference in slope

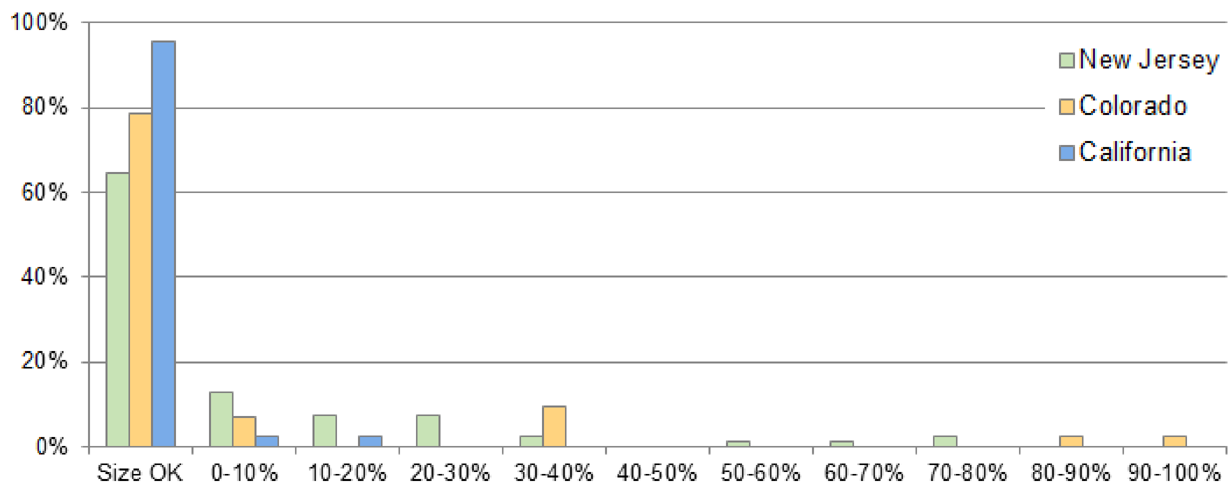

Figure 4. Distribution of difference in size

6 Conclusions

Identifying the amount of rooftop area that is suitable for PV is crucial for conducting several different types of analyses; however, there is no consensus method for estimating that value in the literature. In this report, we provide a review of the literature and building on this review, we present a new method, the "NREL method" for estimating rooftop suitability for PV.

The NREL method presented in this report uses LiDAR and building footprint data from the DHS to model shade, slope, aspect, and size. Our next step is to apply the validated NREL method to data across the more than 120 U.S. cities with available data from the DHS. Ultimately, we intend to employ statistical methods to extend our analysis to other areas across the United States and create a national database of available rooftop space for PV. This database will be useful for estimating rooftop PV market potential to identify promising areas to target and other applications. With the database, users will be able to set thresholds for several criteria. For example, database users will be able to include only areas on rooftops with less than a specified slope or decide whether east- and west-facing roofs should be included with south-facing roofs. This approach taken with the NREL method aims to eliminate some assumptions inherent in much of the literature about ideal placement properties and allow more flexibility in future analyses.

A key distinguishing feature of the NREL method for estimating rooftop suitability for PV is the thorough calibration and validation process we conducted. This report presents our findings from this initial research, which will serve as the foundation for future work on rooftop suitability for PV.

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