Automated quantification of solar photovoltaic potential in cities

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Automated quantification of solar photovoltaic potential in cities

Overview: A new method to determine a city's solar electric potential by analysis of a distribution feeder given the solar exposure and orientation of rooftops.

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Key words: Solar Energy, Photovoltaic, City Planning, Rooftop, Automation, Urban, Urban Planning, Distributed Generation, Renewable Energy, Sustainable Energy

Abstract: Solar photovoltaic (PV) energy conversion offers a sustainable method of producing electricity to maintain and improve the standard of living within cities. Planning for large-scale adoption of PV in cities, however, provides a challenge to urban planners because of the distributed nature of PV. This paper develops a new methodology to determine a city's PV potential by analysis of solar PV generation potential by distribution feeder given the solar exposure and orientation of rooftops serviced by a specific feeder within the city. The methodology is applied to an example feeder, and then can be scaled to apply to the network of any city. The method comprises the following steps: (i) rooftop extraction from aerial photos; (ii) service parcel and territory matching based on geographical information system (GIS) data; (iii) simulation of the solar exposure of the customers connected to distribution feeders based on local meteorological conditions and the general roof orientation of the customers serviced by the feeder; and (iv) sensitivity analyses of electricity yield as a function of PV module efficiency. Experience from the case study such as trade-offs between time consumption and data quality is discussed to highlight a need for connectivity between demographic information, electrical engineering schematics and GIS. Finally conclusions are developed to provide final methodology with the most and useful information from the highest constrained sources and can be adapted anywhere in the world.

1. INTRODUCTION

Solar photovoltaic (PV) energy conversion offers a sustainable method of producing electricity to provide for contemporary society's needs (Pearce, 2002). The advantages of PV in producing electricity include: i) generating no atmospheric emissions or radioactive waste during use, ii) acting as a distributed electrical generation source, iii) assisting in national energy security and iv) improving long-term economic growth (d'Estaintot, 2000). These advantages are made available for any country that aggressively
develops the technology. This has led to international cooperation and technology investment over the past 25 years, which in turn has given rise to fantastic gains in solar PV cell performance and a predicted changing landscape in R&D activities for solar cell technologies (d’Estaintot, 2000; EPIA, 2003; Hoffman, 2006; Green, Emery, et al., 2010). Solar cells made from a variety of materials have demonstrated efficiencies over 10% and are currently manufactured globally. As the technological proficiency of the solar cell industry matured, the total shipments of solar cells increased rapidly. By 2010 about 35 GW have been installed having started out less than 1GW in 2000 with a substantial annual growth rate (IEA, 2011; REN21, 2008; Doty, McCree, et al., 2010). This growth rate, while impressive, must be kept in context of the global energy market. In 2000, the peak electrical generation capacity in the U.S. was 825 GigaWatts (GW = 109W) while the cumulative total global installed solar PV was less than a single GW. In the last four years the market has surged although it is still a tiny fraction of the overall global energy supply.

The increasing technological competitiveness of solar PV, among other kinds of renewable energy technologies, has contributed to a ‘new logic of infrastructure provision’ (Marvin and Guy, 1997) and a ‘paradigm shift in energy policy’ (Helm, 2005). However, in the debates on urban and regional development and regional infrastructure policy, the delivery of utility services still seems to be taken for granted and to be left to engineers, network operators and (supra)-national utility regulators. Consequently, there has been little research on the urban and regional impacts of utility restructuring and the changing environment for urban and regional governance (Marvin, Graham, et al. 1999; Monstad, 2007). In particular for the case of solar PV, its use is still dwarfed, by conventional, centralized and largely fossil fuel-based energy production methods. The limiting factor does not lie with resources to deploy solar PV, but with the appearance of prohibitively high levelized costs of electricity in the conventionally highly-subsidized energy market, lack of scale, and market experience, resulting in a low rate of uptake in absolute terms (Neuhoff, 2005, 2008; Sanden, 2005; Pearce, 2008; Branker, Pathak, et al., 2011). To improve the rate of PV deployment by levelling the economic playing field, governments throughout the world have introduced incentives such as feed in tariff (FIT) programs (Branker and Pearce, 2010; REN21, 2008) and there has been several new methods of financing proposed to increase and speed access to the necessary capital (Branker and Pearce, 2011; Branker, Shackles, et al., 2011). To properly and effectively implement a FIT program, or take advantage of PV technology’s continued price declines in a city, an understanding the urban local potential (roof space and solar exposure among others) is critical for utility planning, accommodating grid capacity, deploying financing schemes and formulating future adaptive policies (Wiginton, Nguyen, et al., 2010).

This paper develops a methodology to determine a city's PV potential: (i) ranking city-owned buildings by solar resource, facility stock and economic potential for PV generation leading to the economically feasible investments in solar PV for the city itself; (ii) analysis of solar PV generation potential by distribution feeder (e.g. 44 kV, 13.8 kV, and 5 kV feeders) given the solar exposure and orientation of rooftops serviced by city using one example feeder with view of applying it to the rest of the network; (iii) give sensitivity analyses on PV technology and efficiency. The methodology presented here forms the next piece in a pyramidal process of accessing solar PV potential from a regional scale
(Wiginton, Nguyen, et al., 2010; Nguyen and Pearce, 2011) and examines the three most popular methods of rooftop extraction for energy planning. This paper then presents a case study as an example of the methodology in Kingston, Ontario. Experience from the case study such as trade-off between time consumption and data quality is discussed to highlight a need for connectivity between demographic information, electrical engineering schemes and geographical information system (GIS) and a typical factor of solar useful roofs extracted per method. Finally conclusions are developed to provide final methodology with the most and useful information from the highest constrained sources and can be adapted anywhere in the world to guide future work.

2. METHODOLOGY

The level, scope and access of municipal GIS data depend on the technical sophistication and the policy of each city. The case study of Kingston, Ontario provides an example of what is typically available, although the challenges presented here serve as a worst case scenario for projects of a similar scope and purpose. The method comprises the following steps: (i) rooftop extraction from aerial photos using ArcGIS version 9.3; (ii) service parcel and territory matching based on Electricity Distribution System (EDS) GIS data; (iii) simulation via PVsyst version 4.37 of the solar exposure of the customers connected to Kingston Hydro’s distribution feeders based on local meteorological conditions and the general roof orientation of the customers serviced by the feeder; and (iv) sensitivity analyses of electricity yield as a function of panel efficiency respectively. The inputs necessary for the analysis are aerial photos of the city and a parcel shapefile of the service territory.

To account for shading manual roof outlining is carried out on aerial photos. The assumptions and technical considerations for rooftop PV were: (i) 0 degree in azimuthal angle, (ii) roofs were either flat (0 degree tilt) or sloped (45 degree tilt); (iii) HVAC and other rooftop obstacles were taken into account and (iv) shading by trees and surrounding buildings were also taken into account. In the absence of HVAC, other rooftop equipment and shading factors, the installable ratios for gabled roof, hipped roof and flat roof are recommended by Suzuki et al. (2007) to be 50%, 62.5% and 100%, respectively. The resultant roof space, which was outlined in consideration of its orientation, rooftop obstacles and potential shading and which was the projected value of the true roof, Ap. It should be noted here that the error in the assumptions governing the azimuthal and roof tilt angles can be easily limited by all PV simulation software. Once extracted into a shapefile, roof space was categorized in terms of tilt angle and circuit number provided by the grid operator. Although this approach is much less complex than remote sensing, computerized image processing and boasts least cost and ease for adaptation, it was expected to be time consuming and supervision intensive, thus providing measure for trade-off in terms of automation, data quality, time and adaptability.
3. CASE STUDY ANALYSIS

3.1 Rooftop extraction

The inputs for roof outlines are aerial photos of the city of Kingston, which were taken between February and September 2008. These are of 5cm in resolution, 1km² in coverage and under NAD1983 UTM 18N coordinate system. A roof print shapefile already exists for Kingston and was provided by Queen's University Map Library. In Figure 1, the service area of the case study region of an individual feeder (104) is shaded light grey and overlaid with the aerial photos and Ap (in pale white line).

![Figure 1. Service area of an individual feeder (104) shaded light grey and overlaid with the aerial photos and third-level outline scheme (in pale white line).](image)

3.2 Service parcel and territory matching

Categorization of roof space according to primary or secondary line and verification of service territory were done using GIS shapefiles on parcels associated with feeder 104 and a territory markup (paper and digital) for primary and secondary circuits of this feeder. It was recognized that the operating system and available GIS data are not yet perfectly compatible, hence transformer symbols on Kingston Hydro schematics were assumed to be associated with the closest distribution line to the civic address listed for each transformer. Any building that fell out of the parcels identified to be serviced by feeder 104 was accordingly eliminated.
3.3 Photovoltaic energy conversion simulation

The primary input for simulation is area, hence any error in rooftop extraction will affect this step. Another assumption was that panels were closely packed on the roof, i.e. no spacing. This assumption was made to determine an absolute highest case PV power impact on the grid. These numbers were later reduced using more common PV system design layouts and socio-economic analysis of the probability that a PV system would be installed by the utility. PVSyst computed incident insolation as comprising of global, beam, diffuse, albedo components on an hourly basis using the default Hay model, however the user can also specify the Perez et al. model, which is more complex but which gives a more detailed and accurate treatment of diffuse radiation on tilted surfaces (Perez, Stewart, et al. 1987; Perez, Ineichen, et al., 1990).

4. RESULTS

4.1 Roof area calculation

Following the methodology in section 2 and applying it to the case study feeder, the maximum area available for PV ($A_{\text{max}}$) was found to be 133,200 m$^2$. This is total projected area of all roofs that fall in the service parcels for feeder 104. Wiginton et al. (2010) determined the total absolute error by running Feature Analyst (FA) compared to $A_{\text{max}}$ is 15%, giving $A_{\text{fa}} = 113,220$ m$^2$. Note that from either $A_{\text{max}}$ or $A_{\text{fa}}$ it is not possible to distinguish between the flat roof areas ($A_{\text{flat}}$) and the tilted roof areas ($A_{\text{tilt}}$). This third method with its attention to detail allowed this, giving $A_{\text{flat}} = 22,050$ m$^2$ and $A_{\text{tilt}} = 21,390$ m$^2$. Therefore $A_p = A_{\text{flat}} + A_{\text{tilt}} = 43,440$ m$^2$ or 33% of the total projected area of all roofs that fall in the service parcels for feeder. This value of about a third may be useful for more general estimates in urban centers where only a projected roof area is available.

4.2 Solar PV yield and system size

From the ArcGIS platform, roof outlines were categorized as flat or sloped and exported separately to an Open Office Spreadsheet, where they were to be binned according to four classes: up to 10kW; from 10kW to 250 kW; from 250kW to 500 kW and over 500kW. These size classifications correspond to Ontario Energy Board and Ontario Power Authority connection policy and pricing categories. The capped area for each class and for each type of panel i) monocrystalline silicon (mc-Si), ii) polycrystalline silicon (p-Si) and iii) thin film amorphous silicon (a-Si) was found by selecting the nominal power mode in the preliminary system design menu of PVSyst. The resultant areas for each class are shown in the Table 1.
Table 1. Baseline areas for different system sizes and technologies

<table>
<thead>
<tr>
<th>System Power [kW]</th>
<th>mc-Si [m²]</th>
<th>p-Si [m²]</th>
<th>a-Si [m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;10</td>
<td>83</td>
<td>95</td>
<td>167</td>
</tr>
<tr>
<td>10 to 250</td>
<td>2083</td>
<td>2381</td>
<td>4157</td>
</tr>
<tr>
<td>250 to 500</td>
<td>4167</td>
<td>4762</td>
<td>8333</td>
</tr>
</tbody>
</table>

For flat roof tops, the majority of potential systems would be built in the 250kW system class, as summarized in Table 2.

Table 2. Total projected area of flat roof by system size and technology

<table>
<thead>
<tr>
<th>System Power [kW]</th>
<th>mc-Si [m²]</th>
<th>p-Si [m²]</th>
<th>a-Si [m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;10</td>
<td>165</td>
<td>266</td>
<td>836</td>
</tr>
<tr>
<td>10 to 250</td>
<td>23869</td>
<td>23768</td>
<td>26078</td>
</tr>
<tr>
<td>250 to 500</td>
<td>2880</td>
<td>2880</td>
<td>---</td>
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</tbody>
</table>

There are no tilted roofs that can fit the larger class of 500 kW systems. As shown in Table 3, more roofs still fall into the category of 250kW system size compared to the 10kW system size; however, the trend is reversed for thin film amorphous silicon panels, as expected since a-Si has the lowest efficiency and hence requires the largest area to attain a given nominal power. It should be noted here, however, that a-Si:H PV output is generally under-predicted by conventional techniques developed on mc-Si/p-Si-based PV technology, because of (1) the superior a-Si:H temperature coefficient (Schwabe and Jansson, 2009; Carlson, Lin, et al., 2010) and (2) the use of integrating photometers such as pyranometers can directly introduce errors up to 20% in the prediction of a-Si:H PV system yearly output due to this spectral effect, depending on seasonal and locational effects (Ruther, Kleiss, et al., 2002; Gottschag, Betts, et al, 2004; Hirata and Tani, 1995; Betts, Jardine, et al., 2005).

Table 3. Total projected area of tilted roof by system size and technology

<table>
<thead>
<tr>
<th>System size [kW]</th>
<th>mc-Si [m²]</th>
<th>p-Si [m²]</th>
<th>a-Si [m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;10</td>
<td>10000</td>
<td>11900</td>
<td>18400</td>
</tr>
<tr>
<td>10 to 250</td>
<td>16100</td>
<td>14200</td>
<td>7700</td>
</tr>
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4.3 Sensitivity analysis on module efficiency

Using RETScreen, different efficiencies were chosen for three technologies: mc-Si 15-20%, p-Si 10-15% and a-Si 6-10%. The nominal output per m² of panels (P_{unit}) was then multiplied with the total area of panels for each type of roof (A_{flat} and A_{tilt}), accounting for optimal tilt (35
degrees) and azimuthal angles (0 degrees) to give the maximum nominal power ($P_{\text{flat}}$ and $P_{\text{tilt}}$):

\[
P_{\text{flat}} = P_{\text{unit}} \times A_{\text{flat}}
\]

(1)

\[
P_{\text{tilt}} = P_{\text{unit}} \times A_{\text{unit}}
\]

(2)

Table 4. The summary of the effect of efficiency on MW yield for the individual feeder.

<table>
<thead>
<tr>
<th>mc-Si efficiency/% kW per m² - Sunpower</th>
<th>E_{flat}/ MW</th>
<th>E_{tilt}/ MW</th>
</tr>
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<tr>
<td>16.9</td>
<td>0.17</td>
<td>4.6</td>
</tr>
<tr>
<td>17.3</td>
<td>0.173</td>
<td>4.7</td>
</tr>
<tr>
<td>18.1</td>
<td>0.181</td>
<td>4.9</td>
</tr>
<tr>
<td>18.5</td>
<td>0.185</td>
<td>5</td>
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<table>
<thead>
<tr>
<th>p-Si efficiency/ % kW per m² - Q Cells</th>
<th>E_{flat}/ MW</th>
<th>E_{tilt}/ MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.4</td>
<td>0.103</td>
<td>2.8</td>
</tr>
<tr>
<td>11.2</td>
<td>0.111</td>
<td>3</td>
</tr>
<tr>
<td>12.6</td>
<td>0.125</td>
<td>3.4</td>
</tr>
<tr>
<td>13</td>
<td>0.13</td>
<td>3.5</td>
</tr>
<tr>
<td>13.6</td>
<td>0.136</td>
<td>3.7</td>
</tr>
<tr>
<td>14.3</td>
<td>0.142</td>
<td>3.8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>a-Si efficiency/ % kW per m² - UniSolar</th>
<th>E_{flat}/ MW</th>
<th>E_{tilt}/ MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>0.07</td>
<td>1.9</td>
</tr>
<tr>
<td>7.2</td>
<td>0.071</td>
<td>1.9</td>
</tr>
<tr>
<td>7.5</td>
<td>0.074</td>
<td>2</td>
</tr>
<tr>
<td>7.7</td>
<td>0.077</td>
<td>2.1</td>
</tr>
<tr>
<td>8</td>
<td>0.08</td>
<td>2.2</td>
</tr>
<tr>
<td>8.2</td>
<td>0.081</td>
<td>2.2</td>
</tr>
</tbody>
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Under the most optimistic case (optimal angles for both tilt and azimuth) and of the most efficient technology (mono-Si, 18.5% efficiency), the area serviced by feeder 104 could expect to generate 5.0 MW from flat roof and 4.8 MW from tilted roof as seen in Table 4. Given the same technology and efficiency, Figure 2 below shows that flat roof yields slightly higher nominal power than do the tilted roof tops and this difference widens with less efficient panels. It should be noted here that this is the largest possible capacity available with current technology. This is also assuming close packing of PV modules. So for example the ratio of MW/acre is
larger than in a traditional ground mounted system because every square meter identified on a tilted roof top as usable area is assumed to be covered with PV. This number represents the baseline for applying other filters such as social/cultural and economic that would restrict the actual installed capacity in the short to medium term.

Figure 2. Nominal power in case study for different panel efficiencies and silicon-based PV technologies

5. DISCUSSION AND FUTURE WORK

GIS techniques have been applied by several authors to study PV deployment and/or impervious urban fabric (Gadsden, Rylatt, et al., 2003; Ghosh and Vale, 2006; Izquierdo, Rodrigues, et al., 2008; Kraines, Wallace, et al., 2001; Kraines and Wallace, 2003; Ryatt, Gadsden, et al., 2001). Image recognition, both object-based and spectrally-based, supervised and unsupervised, has been used as a means of studying urban fabric and determining roof area (Akbari, Shea Rose, et al., 2003; Guindon, Zhang, et al., 2004; Ratti and Richens, 1999; Richens, 1997; Taubentock, Roth, et al., 1999). Unfortunately, this past research is not directly applicable to determining the rooftop PV potential in Ontario for one of the following reasons: (i) the technique was applied a single building, neighborhood or city, not a large-scale region (Gadsden, Rylatt, et al., 2003; Ghosh and Vale, 2006; Ryatt, Gadsden, et al., 2001); (ii) the goal is to classify land use designations rather than extract roof area (Akbari, Shea Rose, et al., 2003; Guindon, Zhang, et al., 2004) or (iii) the input data is different from that which exists for many locations including the case study in Ontario (Izquierdo, Rodrigues, et al., 2008; Kraines, Wallace, et al., 2001; Ratti and Richens, 1999; Richens, 1997; Aramaki, Sugimoto, et al., 2001). In particular, Feature Analyst (FA) has been used in the assessment of buildings and/or land use. Psaltis & Ioannidis (2008) and Ioannidis et al. (2009) used FA in detecting building change in
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Greece, while Yuan (2008) detects land-use/land-cover change. FA has also been used for quantifying impervious land cover for hydrology studies (Kunapo, Sim, et al., 2006), tsunami vulnerability assessments (Sumaryono, Strunz, et al., 2008) and for studying trends in salamander populations (Miller, 2005). None of the work with FA had studied roof area quantification for PV deployment until Wiginton et al. (2010) filled in the gap and discovered a linear relationship between population density and roof area across a region in Ontario. The relationship indicates a total roof area of 70.0 m²/capita ± 6.2%. The training of FA and subsequent error analysis was done using the existent building foot prints, indicating uncertainty.

Although the result of the case study speaks only directly for Kingston, the procedure here is typical of what can be done for an urban setting, especially where there is a dis-connectivity between remote sensed data of different kinds (GIS, satellite, aerial photos and radar) and across sectors (electric grid operation, demographic).

Data quality induced several assumptions and constraints, which provide room for improvement of the methodology:

(i) Digitization is inherently flawed as the human eyes can only see to a certain resolution of the photos, which is equivalent to 20cm on true ground;

(ii) Since supervision was required for every individual house concerning roof type, shaded portion, orientation and inclination, it takes about 2 weeks to process 0.5km² of urban space.

This does not take into account the distortion and multiple view problems arising through merging hundreds of aerial photos into one large tile which also needs to be corrected. While the resultant solar-useful roofprints eliminate shading, which is unpredictable by time of day, month, variable with urban morphology but become relevant as we go down to the household/single system level (Carneiro, C., Morello, et al., 2009) and hence often hard coded as a parameter in simulation, in the process they become static (i.e. cannot be broken down into monthly or daily values) and their accuracy cannot be verified. At the same time neither study found in previous literature of similar scale and approach has yet attempted to take care of shading from surrounding trees and architectural structures (Suzuki, Ito, et al., 2007; Besenićara, Trstenjakb, et al., 2008). In many aspects, the method presented diverges from full automation, which is expected from remote sensing data (e.g. airborne laser scanning), but which is still missing in treatments of utilities scale of km² of land (Pfeifer, M., Rutzinger, et al., 2007).

In addition to the time and labor consumption, final results are dependent on the user's experience, which becomes another uncontrolled uncertainty and which utilities always attempt to minimize. The availability of an airborne laser scanning (ALS) dataset can give hope to solve the misalignment problem, increase the degree of automation, accuracy, efficiency and adaptability. It has been established that building footprints, if up to date and positioning-accurate, can serve as a 'gauge' to extract cloud points corresponding to buildings, which will then be filtered further by using a height that distinguish the rooftop level from any lower objects from within the cloud points (e.g. Pfeifer, M., Rutzinger, et al., 2007; Dorninger, Pfeifer, et al., 2008; Jochem, Hofle, et al., 2009). Indeed, a systematic combination of aerial photos, building footprints and Light Detection and Ranging (LiDAR) backscatter can process twice the size of urban space involving trees and roof configurations of various levels of complexity in half the time (Nguyen, Pearce, et al., 2012). This approach can then be used to account for shading (Nguyen and Pearce, 2012).
LiDAR for this application is extremely promising. Although historically costly, the prices have also come down with time and many cities already have some limited LiDAR data available. Perhaps, even more promising is the recent improvements in software to analyze digital photographs and generate a three-dimensional model of the photos and a point cloud of a photographed object(s). These programs use some version of pattern recognition to compare portions of images to create points (point cloud), which are then compared to convert the image into a model. This true 3-D model can then be used following the example of Nguyen and Pearce to extract real PV potential including near-obstruction shadow losses (2012). Examples of this software technology include, Adobe 123D Catch and Photosynth developed by the University of Washington and Microsoft Live Labs. Both of these tools have been made available for free to users, although there is also work underway for fully free and open-source software tools that can provide the same or better levels of performance. In addition, in order to actually take the necessary number of photographs there has been substantial developments in the open-source hardware community (specifically see DIYDrones.com, openpilot.org, or code.google.com/p/arducopter). These developments enable extremely low-cost small drone camera platforms to automatically photograph sections of cities. In this way point clouds could be created even for substantial cities for very small investments in time, money and labor. Future work is needed for these developments to be integrated into the methodology described here to provide a completely automated high accuracy process for estimating PV energy generation potential from existing city rooftops.

Future work requires practical evidence from local operating systems for an integration of such design aspects as row on row shading for the flat roofs. However, the methodology provided a means of analysis of solar PV generation potential by distribution feeder (e.g. 44 kV, 13.8 kV, and 5 kV feeders) given the solar exposure and orientation of rooftops serviced by a utility using one example feeder with view of applying it to the rest of the network. In addition it also extended the argument on the interaction between urban structures and energy demand made by Madlener & Sunak (2011). Although the current design of cities is responsible for high urban energy consumption, especially in developing countries, the building stock can still be utilized towards a larger share of renewable energy, solar PV-derived electricity in particular, in urban electricity planning given a certain level of technical advancement, appreciation and experience. For existing cities, the case of Kingston has provided a rule of thumb that a value of about a third may be useful for more general estimates in urban centers where only a projected roof area is available. However for emerging (mega)cities the way trees are going to be planted and houses built can affect the uptake of solar energy and its role in the often heavily pressured electricity grid, hence the city’s performance in sustainability, as demonstrated in the breakdown of different roof types for different system sizes and hence potential benefits under the FIT program. This calls for multi-dimensional, participatory and multi-sectoral urban energy planning, whereby a new generation of software and techniques for the purpose of streamlining urban structure extraction for renewable energy assessment can be of great assistance.
6. CONCLUSIONS

The paper has presented a methodology to provide urban solar photovoltaic resource assessments, which is widely applicable throughout the world. The results of the case study presented here indicate that utilities needing to plan for large scale solar electric generation in urban areas can make a rule of thumb estimate. In the absence of advanced computational expertise and high quality remote sensed data, one third of the projected area of roofprints can be used as a first pass estimation of the available area for PV installation. Then simple geometry and potential system specifications can be employed to evaluate the potential solar energy generation. The methodology presented here could be run in a similar case study area in the urban region of interest to reduce error without moving to more complicated, time consuming and costly methods. However only an accurate aggregate assessment can be output in terms of (i) the simulation of the solar exposure of the customers connected to distribution feeders based on local meteorological conditions and the general roof orientation of the customers serviced by the feeder and (ii) sensitivity analyses of electricity yield as a function of panel efficiency. As the required levels of detail, accuracy and flexibility are raised, roofprints will become secondary to a symbiotic relationship between airborne laser scanning, roof segmentation and shading simulation. Thus such rules of thumb will be phased out as the combination of different disciplines (computer vision, solar energy system engineering, spatial analysis) for PV continues to be a proliferate area of research.

7. ACKNOWLEDGEMENTS

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