

Quantifying Rooftop Solar Photovoltaic Potential for Regional Renewable Energy Policy

L.K. Wiginton, H. T. Nguyen, J.M. Pearce

Abstract

Solar photovoltaic (PV) technology has matured to become a technically viable large-scale source of sustainable energy. Understanding the rooftop PV potential is critical for utility planning, accommodating grid capacity, deploying financing schemes and formulating future adaptive energy policies. This paper demonstrates techniques to merge the capabilities of geographic information systems and object-specific image recognition to determine the available rooftop area for PV deployment in an example large-scale region in south eastern Ontario. A five-step procedure has been developed for estimating total rooftop PV potential which involves geographical division of the region; sampling using the Feature Analyst extraction software; extrapolation using roof area-population relationships; reduction for shading, other uses and orientation; and conversion to power and energy outputs. Limitations faced in terms of the capabilities of the software and determining the appropriate fraction of roof area available are discussed. Because this aspect of the analysis uses an integral approach, PV potential will not be georeferenced, but rather presented as an agglomerate value for use in regional policy making. A relationship across the region was found between total roof area and population of $70.0 \text{ m}^2/\text{capita} \pm 6.2\%$. With appropriate roof tops covered with commercial solar cells, the potential PV peak power output from the region considered is 5.74 GW (157% of the region's peak power demands) and the potential annual energy production is 6909 GWh (5% of Ontario's total annual demand). This suggests that 30% of Ontario's energy demand can be met with province-wide rooftop PV deployment. This new understanding of roof area distribution and potential PV outputs will guide energy policy formulation in Ontario and will inform future research in solar PV deployment and its geographical potential.

Keywords: GIS; roof area; Feature Analyst; renewable energy; solar photovoltaic; sustainable future

1. Introduction

Global climate destabilization as a result of the anthropogenic emission of green house gases (GHGs) is one of today's most urgent issues (IPCC, 2007; Jacobson, 2009; Sims, et al., 2007; UN, 1992). Being that more than half of anthropogenic GHG emissions comprise carbon dioxide from fossil fuel combustion (IPCC, 2007), the mitigation of climate change predominantly concerns our energy use. Renewable energy technologies are recognized as a vital part of energy use reform (Jacobson, 2009; Neuhoff, 2005; Pearce, 2002; Sanden, 2004).

In particular, the direct conversion of sunlight into electricity by solar photovoltaic (PV) technology possesses great untapped potential and represents a technically viable and sustainable solution to energy demands (Neuhoff, 2005; Pearce, 2002). The use of PV

power is still dwarfed, however, by conventional (largely fossil fuel-based) energy production methods. In fact, despite staggering growth rates of 110% in the last year (Solarbuzz, 2009), PV accounts for less than 1% of the global energy supply (IEA, 2008a). Resources to deploy solar PV are not the limiting factor: PV remains an "infant technology" primarily because of its prohibitively high levelized cost of electricity and lack of market experience, resulting in a low rate of uptake in absolute terms (Neuhoff, 2005; Pearce, 2008; Sanden, 2004). To improve the rate of PV deployment, governments throughout the world have introduced incentives such as Ontario's pending feed in tariff (FIT). The Ontario FIT is predicted to increase the uptake of PV across the province; in particular, it will encourage rooftop PV deployment as a result of its sliding-scale pricing structure (OPA, 2009). Yet, the maximum energy potential if PV is deployed on every appropriate rooftop in the region remains unknown because data concerning roof area in most regions simply does not exist. Understanding the rooftop PV potential is critical for utility planning, accommodating grid capacity, deploying financing schemes and formulating future adaptive policies.

In order to overcome these challenges, this paper will merge geographic sampling with object-specific image recognition to determine the available rooftop area for PV deployment in a large-scale region in south eastern Ontario, referred to as the "Renewable Energy Region (RER)" (Mabee and Carpenter, 2009). It will apply the Visual Learning Systems' ArcGIS extension, Feature Analyst, to produce advanced feature classification algorithms for extracting rooftop features from batches of high-resolution digital orthophotos. Limitations of the product for this application will be discussed. From this rooftop extraction on a representative geographical sample of the region, the relationship between population and roof area will be explored and extrapolated to the entire region. Relating roof area to population will be shown to be highly important, not only for understanding the rooftop PV potential, but also with regards to other applied urban sustainability initiatives such as solar thermal heating, green roofs and stormwater runoff management.

From total roof area, an estimate of rooftop PV potential will be produced by considering factors such as shading, other uses, and orientation of rooftops, PV panel efficiencies and average solar insolation in the region. Because this aspect of the analysis uses an integral approach, PV potential will not be georeferenced, but rather presented as an agglomerate value for use in regional policy making. Power and energy outputs will be compared to provincial and regional demands. These important and previously unknown figures can be used to direct government, banking and utility-related policy in Ontario immediately and in the future.

The focus of this paper is on the development of an approximation of total roof area. A separate simulation for determining PV potential from total roof area was outside the scope of this project as it is highly location dependent, thus, methods were taken from the literature. Future research can expand upon these aspects of this paper's results.

2. Background

2.1 Related Work

Several authors have applied GIS techniques to the topic of PV deployment and/or impervious urban fabric (Gadsden et al., 2003; Ghosh & Vale, 2006; Izquierdo et al., 2008; Kraines et al., 2003; Kraines et al., 2001; Rylatt et al., 2001). Image recognition, both object-based and spectrally-based has been used as a means of studying urban fabric and determining roof area (Akbari et al., 2003; Guindon et al., 2004; Ratti & Richens, 2009; Richens, 1997; Taubenbock et al., 2008).

Unfortunately, this past research is not directly applicable to determining the rooftop PV potential in Ontario for one of the following reasons: (1) the technique was applied a single building, neighbourhood or city, not a large-scale region (Gadsden et al, 2003; Ghosh & Vale, 2006; Rylatt et al., 2001); (2) the goal is to classify land use designations rather than extract roof area (Akbari et al., 2003; Guindon et al., 2004) or (3) the input data is different from that which exists for Ontario (Aramaki et al., 2001; Grosso, 1998; Izquierdo et al., 2008; Kraines et al., 2003; Kraines et al., 2001; Ratti & Richens, 1999; Richens, 1997).

In particular, Feature Analyst (FA) has been used in the assessment of buildings and/or land use. Psaltis and Ioannidis (2008) and Ioannidis et al. (2009) use FA in detecting building change in Greece, while Yuan (2008) detects land-use/land-cover change. Feature Analyst has also been used for quantifying impervious land cover for hydrology studies (Kunapo, 2006), tsunami vulnerability assessments (Surmaryono et al., 2008) and for studying trends in salamander populations (Miller, 2005). None of the work in FA to date, however, has studied roof area quantification for PV deployment.

Further, several authors have explored the relationship between population and roof area in Brazil (Ghisi, 2006), Germany/Western Europe (Lehmann & Peter, 2003), India (Kumar, 2004; Pillai & Banerjee, 2007), Spain (Izquierdo et al., 2008) and the United Kingdom (Pratt, 1999). Guindon et al. (2004) have studied the relationship between building density and population density in Canada; however, they did not study roof area in particular. In addition to the improvements in methodology, this paper will contribute to this literature by exploring population-roof area relationships in the province of Ontario, Canada and identifying similarities and differences to other regions.

2.2 Government Incentives for Renewable Energy

Governments have an important role to play in reducing GHG emission trends (IEA, 2008b). By using careful policy measures, governments have the means to increase the

uptake of PV, thereby spurring associated innovation and increasing economic competitiveness through economies of scale (Sanden, 2004; Pearce, 2008). By increasing reliance on distributed sources of renewable sources of energy, particularly roof-mounted PV, governments of any size possess the power to reduce their regions' environmental impact through a reduction in GHG emissions from carbon use (Pearce, 2002; Caamaño-Martín, 2008; Herig, 2003; IEA, 2008b). Further, renewable energy technologies address regional and national security (IEA, 2008b) in that they decrease reliance on other regions for energy sources, particularly fossil fuels (Pimentel et al., 1994; Caamaño-Martín, 2008), and can also provide greater reliability during times of high demand and pending blackouts (Caamaño-Martín, 2008; Herig, 2003; Perez & Collins, 2004). Additionally, renewable energy technologies facilitate the establishment of distributed generation which reduces transmission and distribution costs as well as system losses (Caamaño-Martín et al., 2008; Pearce and Harris, 2007; Shalaby, 2008). Finally, renewable energy technologies eliminate the need for the construction of new large-scale fossil fuel power plants and the associated economic risks that accompany these projects (Caamaño-Martín, 2008; Pearce and Harris, 2007; Shalaby, 2008). Overall it can be seen that there are many reasons for which governments have an interest in the expansion of distributed generation of renewable energy such as roof-mounted PV in their regions.

2.2.1 Feed-in Tariffs

Feed-in tariffs (FITs) have proven to be the most effective government incentive program for renewable technologies: countries who have adopted FITs have been shown to have the largest growth rates in renewable energy technology deployment (Pietruszko, 2006; REN21, 2009; EPIA, 2008). In fact, half of the world's PV installations are due to FITs (Peters & Weis, 2008). FITs for PV are being utilized around the globe: in early 2009, 45 countries and 18 states/provinces/territories had FITs (REN21, 2009). In Germany, a FIT program has been offered to PV operators for nearly two decades. The tariff is altered throughout the years to spur innovation and effectively stimulate the market (EEG, 2007). The success of the FIT enabled Germany to reach its goal of having a 12.5% renewable energy supply three years early, in 2007 (EEG, 2007; Peters & Weis, 2008) and encouraged 18 other EU countries to adopt similar programs (EEG, 2007). Another country to successfully pursue FITs was Spain: in 2008, Spain saw a five-fold increase in PV capacity from the previous year. Germany and Spain possessed 5.4 and 3.3 GW of PV power capacity in 2008, representing the majority of the world's 13 GW total (REN21, 2009). Other countries/regions with FIT programs include California, Ireland, Portugal, the Slovak Republic, Switzerland, Turkey, Bulgaria, Greece, France, Kenya, the Philippines, Poland and South Africa (REN21, 2009).

2.2.2 The Ontario FIT

The province of Ontario, Canada has committed to phasing out the use of all coal-fired plants by 2014 (OPA, 2009a). The Ontario legislature has passed the Green Energy Act 2009 (REN21, 2009) which includes provisions for a new FIT renewable energy incentive program (OPA, 2009b). Through the FIT, owners of renewable energy technologies will enter into a 20-year contract with the power authority whereby they will be paid a fixed amount per unit electricity fed to the electrical grid. For residential PV applications under 10 kW in size, owners will be paid CAD\$0.802 per kW (OPA, 2009b). The tariff prices are set on a sliding scale such that they provide a greater economic incentive for small scale, rooftop PV installations over large, ground-mount systems in order to equalize the rate of return. The initiative is highly ambitious and is set to establish Ontario as "North America's leader in renewable energy" (OPA, 2009c).

Because of the success of FIT programs in Germany, Spain and several other countries (EEG, 2007; Peters & Weis, 2008; REN21, 2009), Ontario's progressive FIT is predicted to increase the uptake of PV across the province; in particular, it will encourage rooftop PV deployment as a result of its sliding-scale pricing structure. The maximum potential if solar PV is deployed on every appropriate rooftop in the region, however, remains unknown because data concerning roof area in most regions simply does not exist. Understanding the rooftop solar PV potential is critical for utility planning, accommodating grid capacity, deploying financing schemes and formulating future adaptive policies. This paper uses geospatial computer-based techniques to address the need to quantify the solar PV potential in Ontario with the goal of producing informed and effective policy.

2.3 Region of Study

The Renewable Energy Region (RER) comprises the south eastern region of the province of Ontario, Canada. Seen in Figure 1, the region extends east to Ottawa (Canada's capital city), north to Algonquin Provincial Park, south to Lake Ontario, and west to Peterborough, stopping before the Greater Toronto Area. The RER has a total land area of 48 000 km² and a total population of 1.9 million people as of the 2006 census, comprising 16% of Ontario's population (StatsCan, 2009). The region consists of 14 census divisions and 109 census subdivisions. The three largest cities in the region are Ottawa, Kingston and Peterborough, with populations of 812 000, 117 000 and 75 000 respectively in 2006 (StatsCan, 2009).

The RER was selected to match the Ontario East Economic Development region as outlined by the Ontario East Economic Development Commission (OEEDC, 2006). Prominent industries in the region include agriculture, manufacturing, biotechnology, business process outsourcing, food processing, information and communications technology, logistics and distribution, plastics and tourism (OEEDC, 2006). There is also

a growing bioenergy industry which has large support from the provincial government (OEEDC, 2006).

One aspect which differentiates Canada from much of the rest of the world is its relative abundance of open, undeveloped and sparsely populated land. This characteristic has a large influence on the work and methods contained in this paper. In the RER, the majority of the population is situated along what is known as the Toronto-Ottawa corridor which runs along the southern-most part of the region. North of this corridor, the region is typified by farmland; further north still, the land becomes less agriculturally suitable and thus the region is largely forested.

The determination of solar rooftop PV potential will contribute to a larger-scale research initiative being conducted by the Queen's Institute of Energy and Environmental Policy (QIEEP) for the RER. QIEEP is investigating the policy changes needed in order to render this region an overall net producer of renewable energy. This involves research regarding potential for biomass, wind, hydro, ground-mounted solar PV farms, and solar rooftop PV power. The region possesses abundant renewable resources and is already on its way to becoming a net producer of renewable energy (Mabee and Carpenter, 2009). There is a need to understand these different resources in order to formulate appropriate policy which moves south eastern Ontario toward energy sustainability. This paper will provide the rooftop solar PV piece to this greater research initiative.

2.4 Available Data

The availability of high quality GIS data played the strongest role in determining the methodology used for this research. Canada's GIS data is often inconsistent across large regions, and due to the vast and open nature of the Canadian landscape and the dependence of the Canadian economy on primary resources such as forests and minerals, the data often focuses on coarse land classifications such as soil type or forest coverage. Compared to Japan or Europe (Aramaki et al., 2001; Izquierdo et al., 2008), urban land use classification is significantly underexploited whether by means of orthophoto recognition and extraction or reconstruction from LIDAR/ GoogleEarth.

Census data from Statistics Canada was utilized to determine land area and population for each of the region's census subdivisions. This data is publicly available online (StatsCan, 2009). GIS datasets containing the related administrative boundaries were obtained through the Maps, Data and Government Information Centre at Queen's University (Queen's University, 2008).

In Canada, municipalities occasionally obtain roof print data for their own use. This is typically done in large municipalities with adequate funding and aerial imagery. Roof print shapefiles consist of the outline of all buildings from an aerial view which have

Published in: L.K. Wiginton, H. T. Nguyen, J.M. Pearce, "Quantifying Solar Photovoltaic Potential on a Large Scale for Renewable Energy Regional Policy", *Computers, Environment and Urban Systems* 34, (2010) pp. 345-357. <http://dx.doi.org/10.1016/j.compenvurbsys.2010.01.001>

been digitized manually, thus giving the outputted shape files a high degree of accuracy. Within the RER, roof prints were available for Kingston, Peterborough, and a small portion of the City of Ottawa, however the majority of the Ottawa district was unavailable.

Finally, a new aerial imagery project titled the Digital Raster Acquisition Project – East (DRAPE) has emerged for south eastern Ontario. DRAPE is a public-private collaboration administered by Land Information Ontario (Groupe Alta, 2008). When complete, DRAPE will be a database of 20 cm-resolution digital orthophotos for the region matching the RER in colour, black and white, and near infrared (MNR, 2009). At the time of this research, only small segments of the DRAPE database were available.

The roof print and DRAPE data were provided by the Maps, Data and Government Information Centre at Queen's University (Queen's University, 2008) from the Ontario Ministry of Natural Resources in Peterborough, Ontario.

3. Methodology

A five-step procedure is used in this paper in the analysis of available rooftop PV potential, as seen in Figure 2. This methodology demonstrates techniques and principles in a step-wise manner that may inform the determination of roof area available for PV in other initiatives.

First, the RER is segmented into administrative boundaries so that land area, population and population density information can be easily obtained for smaller geographical units within the region. These smaller entities are used as the sampling units for Step Two, where roof areas are obtained for 10 of the administrative divisions through automated feature extraction techniques. Next, in Step Three, this sample information is extrapolated to represent the entire region, yielding an estimate of total roof area for south eastern Ontario. In Step Four, the total roof area is reduced to represent available roof area for PV deployment. From this, an estimate of total power and energy output is obtained which can be compared to the demands of Ontario and specifically of the region of interest.

3.1 Division into Geographical Units

In order to begin the analysis of rooftop area, it is necessary to divide the region into smaller geographical units. The administrative boundary of census subdivisions (CSDs), which represent municipalities, Indian reserves, Indian settlements and unorganized territories, is selected for this purpose. Administrative boundaries were obtained in vector shapefile format and were tailored to fit the RER. A similar municipal

geographical unit was chosen by Izquierdo et al. (2008) in their analysis of solar rooftop PV potential in Spain.

The CSD is chosen because land area, population and other types of data are readily available for these areas from the Statistics Canada census information database. The CSD is the smallest administrative division that exists continuously across the region and is larger than a city block (MADGIC, 2009). There are 109 CSDs within the region of interest which together make up the entire region and do not overlap. The CSDs which comprise the RER are seen in the inset in Figure 1.

3.2 Sampling

Ten of the 109 census subdivisions are sampled to determine the relationship between population and roof area. The roof extraction procedure, which involved the use of the Feature Analyst image recognition program, has not been used previously for PV quantification. A description of the sampling process follows.

3.2.1 Roof Print Data

As discussed previously, hand-digitized roof print data exists only for Kingston, Peterborough and a small segment in the downtown core of Ottawa. For Kingston and Peterborough, this previously delineated area has been used to determine available roof area. However, a more inventive method of information gathering must be used for the large remaining portion of the region.

3.2.2 Image Recognition Program and Input Data

Visual Learning Systems' Feature Analyst (FA) is an advanced feature extraction program which exists as an extension to ArcGIS. FA was chosen for its simple and easy-to-learn user interface, behind which lie complex classification algorithms. FA is an object-specific image recognition software which utilizes spectral and spatial information through advanced feature classification algorithms. FA incorporates a machine learner function whereby the researcher "trains" the program to recognize certain features within the image, based on their colour, size, shape, texture and orientation. Other important capabilities of FA that are critical to this research include its aggregation and smoothing mechanisms and its ability to classify batches of images simultaneously using transferable classification algorithms (VLS 2008; VLS 2007). FA is felt to be a highly accurate substitute for the labourious nature of hand-digitization and the complexity of programming new, customized image recognition capabilities (O'Brien, 2003).

DRAPE orthophotos were used as the input data to FA. Being a non-overlapping set of 1 km² square tiles, of high resolution (20 cm) and georeferenced, they were found to be very compatible with FA operations. Altogether, 2036 DRAPE photos were used.

Under the Universal Transverse Mercator (UTM) projection, the RER sits in Zones 17 and 18N for the Northern hemisphere. The datum is North American Datum 1983 (NAD83). The DRAPE photos, which exist in GeoTiff format, were found to align with the projection. Hence, unless otherwise indicated, all input and output is conducted in UTM 17N and 18N NAD83.

3.2.3 Sample Selection

Two main factors affect the selection of census subdivisions for sampling. First, the DRAPE database covers only a portion of the region at the time of the writing of this paper. Thus, researchers are limited to census subdivisions which fall within the DRAPE area.

A second factor in the selection of CSDs is the population density. A number of researchers (Izquierdo et al., 2008; Lehmann & Peter, 2003; Naroll, 1962; Pratt, 1999; Taubenbock et al., 2008) have identified a relationship between population density and roof area. Thus, it is important to investigate trends in both sparsely and densely populated areas of the region. In order to select a representative sample, CSDs were grouped according to population density into three categories: low (0-100 persons/km²), medium (100-500 persons/km²) and high (above 500 persons/km²). It should be noted that of the 109 CSDs, 89 are of low density, with an average density of 21.4 persons/km². Only five are of medium density with an average density of 227.6 persons/km², while 15 are of high density with an average density of 827.3 persons/km². CSDs were then chosen to represent this distribution, drawing from the low, medium and high categories. Table 1 lists the selected CSDs and their population density categories. As well, it provides a description of the settlement typology as shown by the DRAPE images in that area, in order to illustrate the differences in land use across selected CSDs.

It is also informative to note the highly dispersed nature of Canadian settlements compared to other parts of the world, a difference which will affect the available roof area. As a comparison, the "low density" category used in Spain by Izquierdo et al. (2008) comprises regions ranging from 1-2400 persons/km², and some municipalities reach densities higher than 7800 persons/km².

3.2.4 Urban/Suburban Feature Extraction

The very different nature of urban and rural areas required the development of a separate workflow for each. Here it should be noted that the term “urban” is used loosely to describe areas where the land is covered by more buildings than open space; it does not refer specifically to urban areas designated by Statistics Canada. For this paper, the FA extraction tool is used only for “urban” areas and has been found to be most effective in identifying residential buildings. Rooftops which were systematically missed by the learner (large, flat, grey buildings), as well as rooftops in rural areas, are outlined by hand-digitization in ArcGIS. The following sections describe the procedure and challenges faced in working with FA. The entire procedure used to extract buildings from photos is described in Figure 3.

The FA extraction tool works through the creation of a training set on a sample DRAPE orthophoto. An orthophoto (1 km² in size) is chosen that is felt to be representative of the building typologies of the census district. Over the photo, the researcher hand-digitizes 60-70 rooftops as the training set. The training set should encompass a variety of roof colors and types to avoid mis-recognition. In effect, the 'learner' is given a defining range of roof configurations to develop a suitable classification scheme (VLS 2008; VLS 2007).

When training FA to extract features, the user must choose from a number of algorithms, input representations and tools. Using trial and error, sensitivity analyses and FA documentation (VLS, 2007), a simple “Manhattan” input representation pattern with a pixel width of five pixels has been chosen. As seen in Figure 4, the machine learner analyzes the 12 surrounding pixels in order to analyze the pixel of interest (marked with an ‘X’). Using this input representation, FA generates a new shape file which attempts to capture all of the rooftops in the photo.

Next, an aggregation mechanism is used, whereby polygons or holes smaller than 750 pixels in size are merged or eliminated. This helps to smooth the features and remove elements of clutter.

The user may alter the training set several times until the machine learner produces a feature extraction set which is satisfactory. The final feature classification algorithm, which is associated with the training set, may then be saved as an “automated feature extraction” (AFE) file. Figure 5 demonstrates the output of an AFE run on a suburban area in the CSD of Cobourg where FA buildings output are seen in white, hand-digitized additions are seen in grey (online: FA buildings are red, hand-digitized in yellow).

Although FA is also capable of running multiple input representations, hierarchical learning through trained clutter removal, and squaring of features, which render the resulting shape file more visually pleasing, these operations were found to reduce the

accuracy of the results. In addition, the use of a simple process, consisting of one basic input representation followed by an aggregation step, was able to reduce the processing time per orthophoto significantly. Miller (2005) also found that excessive hierarchical learning steps improved the individual training set, but decreased the extraction accuracy overall.

After the creation of an effective AFE file, batch classification of all photos in the set is carried out in order to reduce extraction time. Output files are polygon shapefiles. An unfortunate limitation to batch classification is that FA does not contain the capabilities to apply a mask to the photos when using a batch approach. A mask tells the AFE to ignore regions within or outside of the mask file, hence narrowing the area to be processed and reducing the incidence of false feature extraction. The application of such a technique could have been effective in eliminating roads, for example.

Finally, the resulting roof print layers are examined and manual cleaning is carried out. Manual cleaning consists of using the Edit and Select tools to select and delete features such as roads, parking lots and vegetation which have been falsely classified as rooftops. Although in some cases the manual cleaning operations represented a large proportion of the overall processing time; they were necessary for increased accuracy.

While FA is an extremely powerful tool, it presents some difficulties in building extraction for two main reasons. First, there is a large variation in roof types within cities and neighbourhoods. The roof type in new suburban developments differs greatly from that in older, more mature downtown neighbourhoods, for example. Secondly, there are spectral similarities between features which *are* rooftops and features which *are not*. For example, shades of grey in pavement are spectrally similar to the flat, grey tops of commercial and industrial buildings. Thus, a trade off is necessary between the inclusion all buildings and the associated production of a large number of false positives, or, the exclusion of problematic shades of colour while overlooking some buildings in the process. Where necessary, buildings of these particular colours were excluded from the training layer in order to produce minimal false features. The result is a generally conservative estimate of total rooftop area.

In addition, a difference in roof configurations was seen across CSDs. An AFE developed for the CSD of Cornwall, for example, was found to lose accuracy when applied to a different CSD such as Kingston, producing errors of up to 60%. Miller (2005) also found degradation in AFE accuracy with distance. This inconsistency is believed to be due to the fact that the DRAPE imagery has been collected over a period of time. A minimal change in sunlight or cloud cover can have a significant effect on the spectral nature of the image. Secondly, as previously discussed, different regions have different histories, ages and building typologies associated with them. Thus in order to

maintain accuracy, a new, local AFE has been developed for each district of analysis to account for the different typologies within it.

Although these limitations with FA exist, it was overall found to be a well-suited tool to the analysis. By avoiding problematic shades where necessary and developing CSD-tailored AFEs, the challenges presented by the program were mitigated in a way that produced satisfactory results.

3.2.5 Rural Feature Extraction

As discussed, the learning algorithm encountered a difficulty in distinguishing certain types of rooftops from spectrally similar fields. This presented a large problem in rural areas, where building density is very low and there few buildings per photo, with prolific fields and vegetation. It was determined that to run the photos through the AFE and also undertake the cleaning procedure was more time consuming than to simply create these features manually; thus, all photos considered rural are hand digitized, whereby the Edit and Sketch tools are used to outline each building as a new feature.

3.3 Extrapolation

In order to relate the roof area of the sampled CSDs to the entire region, roof area for each CSD is plotted against its population. It is well known that roof area shares a correlation with population (Ghisi, 2006; Izquierdo et al., 2008; Kumar, 2004; Lehmann & Peter, 2003; Naroll, 1962; Pillai & Banerjee, 2007; Pratt, 1999; Taubenbock et al., 2008). In fact, Guindon et al. (2004) confirm a “high correlation” between building density and population density in Canada. Because of the inconsistent distribution of built-up areas across the region, population is indeed the best indicator of the distribution of roof area (although others could be explored in future work).

From the roof area-population relationship in the sample CSDs, an approximate value of roof area per capita may be determined ($A_{roof/cap}$). Then, roof area across the region (A_{roof}) may be extrapolated across the RER, using population (p):

$$A_{roof} = (A_{roof/cap}) * p \tag{1}$$

This gives an estimation of the gross roof area for the whole of the RER.

3.4 Reduction

Having obtained total roof area for a region, it is necessary to reduce this area to that which is available for solar photovoltaic applications, in order to determine potential power output. There are many factors which influence the fraction of available roof area, including: (1) shading, from other parts of the roof or from neighbouring buildings and trees; (2) the use of roof space for other applications, such as ventilation, heating/air conditioning, dormers or chimneys; (3) the orientation of pitched roofs; and (4) the installation and racking of the PV panels themselves. In Canada, most residential homes possess pitched roofs. In this case, the PV-appropriate roof space is that which faces generally south.

The primary focus of this paper is to develop a careful estimate of the total roof area in the region; a separate simulation or statistical analysis for obtaining reduction factors was outside the scope of the project and thus related literature was utilized to obtain approximate areas available for PV. Table 2 summarizes the fractions of available roof area found by other research initiatives which were felt to be appropriate analyses with which to compare, and indicates how these values were determined. In each case, the researchers multiply the total roof area by the reported fraction to obtain roof area available for PV deployment, taking into account the factors reported in the Table 2.

These fractional coefficients must be compared carefully as they are obtained under different criteria in different regions. However, they give important clues as to appropriate approximate values of roof area reductions. As described in Table 2, these reductions are used to account for shading, other roof uses, insolation patterns and building orientation in various combinations. Those which are most informative in this case are those which account for all sources of reduction. For these purposes of this analysis, the most conservative estimates of roof area reductions from the literature are used. Future research may modify this step to suit other intended uses or analyses.

The reduction process for this analysis was determined as follows. First, building orientation must be accounted for. On average, approximately one quarter of total roof area was comprised of large, flat buildings ($r_{flat}=0.25$). These buildings will undergo no reduction for orientation since they do not possess peaked rooftops and are therefore unaffected by orientation ($f_{flat}=1$) (reductions for panel installation and other factors will be accounted for in the second reduction factor). Residential and other small buildings with peaked rooftops, which constitute the remaining buildings ($r_{peak}=0.75$), will be considered to have 50% south-facing area on average ($f_{peak}=0.5$). Thus is obtained the fraction of properly oriented roof area, f_o :

$$f_o = f_{flat} * r_{flat} + f_{peak} * r_{peak} = (1*0.25+0.5*0.75)=0.625 \quad (2)$$

Next, shading, other uses, and installation must be accounted for. As this analysis aims to be as conservative as possible, the lowest fraction from the literature listed in Table 2 will be applied. This allows for the calculation of the fraction of unshaded roof area which is unused for other purposes, including panel servicing and installation. This fraction, f_s , is therefore taken as:

$$f_s = 0.30 \quad (3)$$

Thus, the roof area available for PV (A_{PV}) is the total roof area (A_{roof}) reduced by the product of f_o and f_s :

$$A_{PV}/cap = (A_{roof}/cap) * f_o * f_s = (A_{roof}/cap) * 0.19 \quad (4)$$

And, using population across the RER to extrapolate:

$$A_{PV} = (A_{PV}/cap) * p \quad (5)$$

This represents the total roof area which is available and appropriate for PV deployment in the RER.

3.5 Conversion

Finally, an estimate of potential power and energy output from the deployment of rooftop PV in south eastern Ontario may be obtained. The potential power and energy output relies heavily on the type of photovoltaic panels used since variations in efficiency of more than a factor of two exist across materials and manufacturers. As such, the analysis has been carried out with four different types of photovoltaic panels readily available on the market: (i) crystalline silicon, (ii) multi-crystalline silicon (often referred to as polycrystalline on the market), (iii) amorphous silicon multi-junction, and (iv) thin-film polycrystalline silicon (also called micro-crystalline or nano-crystalline in the literature). These four types of cells have markedly different efficiencies (summarized in Table 3) and are used to showcase various deployment scenarios.

Potential power output may be calculated as:

$$P = I_g * e * A_{PV} \quad (6)$$

where I_g is the solar global insolation based on the Global Air-Mass 1.5 Spectrum of 1000 W/m² and e is the module efficiency (Green et al., 2009).

Total annual energy output is calculated as:

$$E = I_{md} * 365 * e * A_{PV} \quad (7)$$

Where I_{md} is the mean daily global insolation on a horizontal plane, calculated as an annual average, of 3.3 kWh/m² (NRCan, 2007) and e is the module efficiency (Green et al., 2009).

4. Results

4.1 Total Roof Area

The methodology outlined in Figure 2 was followed for the RER. After geographic division and sampling of the CSDs, roof area was plotted against population in order to determine the relationship for use in extrapolation. Across the 10 sample CSDs, a constant linear relationship between population and roof area is observed, as seen in Figure 6. As shown in Figure 6, the linear relationship holds with an R-squared value of 0.993, indicating a strong correlation across both large and small census subdivisions. The relationship indicates a total roof area of 70.0 m²/capita \pm 6.2%, for use in equations (1) and (4), plus a base, b , of 237 000 m² for the region. This analysis has a 95% confidence interval. The base (intercept) may be explained by infrastructure, such as utilities, in place even in small communities regardless of the number of inhabitants. It is seen, however, that on the large scale of the region, 237 000 m² is well within the error and is thus a negligible corollary of producing the line of fit. Thus, in the proceeding analyses the base will be disregarded.

A comparison of this value to other regions suggests that 70.0 m²/capita is a very reasonable estimate of roof area per person in the Canadian context. Izquierdo et al. (2008) report a range of 24.4-180.5 m²/capita for the country of Spain before reducing for shading and other uses. For the country as a whole, 41.7 m²/capita is reported. In Brazil, Ghisi (2006) has found a range of 17.6-21.2 m²/capita of total roof area, determined during a study for rainwater catchment opportunities. Finally, Pratt (1999) reports a range of 10.6-30.7 m²/capita in the United Kingdom, also in a study of stormwater runoff. Each of these values is compares reasonably given the differences in building density and sprawl between Canada and European/South American countries.

It should be understood that 70.0 m²/capita \pm 6.2% of total roof area is a coarse, overall value *meant to be applied to the RER as a whole*. To see why this is important, the delineation of the census subdivisions must be examined. In most cases, as in Kingston for example, the border of the census subdivision is large and contains the dense downtown region surrounded by suburbs and then by rural farmland. Other census subdivisions have been delineated directly around the dense urban area, while others

comprise nearly all rural farmland. The mix of settlement types within the study area means that the relationship between population and roof area is an overall approximation for the combination of these different land uses.

For analyses on a smaller, more specific scale, there in fact exists a more subtle relationship: with increasing population *density*, a decline in roof area *per capita* is seen. This has been confirmed by work from several authors, including Izquierdo et al., (2008), Lehmann & Peter (2003) and Pratt (1999). Others have investigated this relationship inversely to infer population density from roof areas in present-day developing regions (Taubenbock et al., 2008) and during antiquity (Naroll, 1962).

Lehmann and Peter (2003) have studied this relationship most closely. Plotting values obtained for many sites in Germany, they show that for non-residential buildings, roof area per capita decreases with a cubic function as population density increases. Residential buildings, on the other hand, show a decreasing quadratic function.

In Figure 7, population density is plotted against roof area per capita for each individual census subdivision. It is clearly seen in Figure 7 that as the population density increases the roof area per capita decreases. While 10 data points is not sufficient to obtain a precise function to describe this complex relationship, this graph does demonstrate the value in examining the relationship between population density and roof area per capita for smaller scale analyses. In particular, it is seen that for the low density CSDs (1-100 persons/km²), the average total roof area value, 124.7 m²/capita, is a more accurate representation. Further, when an analysis was conducted on the much higher density downtown core of Ottawa (data for the entire CSD was unavailable), it was found that value closer to 50 m²/capita was more representative. Thus, it is suggested that when analyzing smaller segments of towns, cities, or individual municipalities, the population density should lie between 100-1500 persons/km² in order to use the overall value of 70.0 m²/capita.

Finally, the roof area per capita is extrapolated across the RER using equation (1), giving a value of 134 000 000 m² ± 6.2%. This value is of use to many fields of applied sustainability and urban and regional planning.

4.2 Solar PV Available Roof Area

This total roof area must be reduced to that which is available for PV applications, as discussed in Section 3.4. If total roof area per capita, $A_{\text{roof/cap}}$, is equal to 70.0 m²/capita ± 6.2%, then area available for PV per capita, $A_{\text{PV/cap}}$, using equation (4), is 13.1 m²/capita ± 6.2%, which remains a considerably high value.

Next, this available roof area is extrapolated across the RER using equation (5), giving a value of 25 000 000 m² ± 6.2%. This represents the total roof area which is available and

appropriate for PV deployment in the RER in that it is free of shading and other uses and is oriented generally south.

4.3 Power and Energy Potential

Equations (6) and (7) are then used to approximate the potential power and energy outputs from this distribution of roof area; results are presented in Table 3. As seen in Table 3, potential output from the large-scale deployment of rooftop PV is large: with the more efficient crystalline-silicon panels, 3620 kWh/capita of energy can be produced annually. In 2005, the OPA reported an annual per-capita total (all industries) energy use of approximately 12 000 kWh (OPA, 2009d), and an average annual household energy use of 10 000 kWh (ICF Consulting, 2005). This indicates the considerable contribution that rooftop PV can have to the Ontario grid. Further comparison of outputs to demands will be detailed in Section 5.

4.4 Error

Some sources of error in this analysis relate to data sources which themselves contain a small but unknown error: census data for population and population densities, hand-digitized roof print data from two municipalities, solar insolation estimations and PV system efficiency values. Within the analysis itself, the two main sources of error are the error accrued during the FA building extraction procedure and the standard error on the linear regression model.

The CSD of Kingston offers a unique opportunity for assessing extraction error analysis because both pre-digitized roof print data from the City and DRAPE orthophotos exist. To assess the error accrued using FA, 10 individual orthophotos from Kingston were run through the building extraction workflow; next, the resulting shape files were compared to the roof print data obtained from the City for that photo area. The total rooftop area extracted for each orthophoto by FA was tabulated as a percentage of the "true" rooftop area (i.e. the area indicated by the pre-digitized roof print data offered by the City).

The average absolute error in building extraction on the 10 orthophotos examined was found to be 15%. This represents the error on each data point and denoted by the error bars in Figure 6. Due to the available resources, it was not possible to carry out a consistent analysis on more samples. However, given that the error determined in this fashion has a direct dependency on the number of samples chosen, in the future a larger sample size would certainly contribute to a reduction in error.

It is important to note that although the average *absolute* error found in this analysis was 15%, the average error accounting for negative/positive error is 2%. Therefore, the

extraction error over entire census subdivisions may have canceled out to a significant degree. This is to some extent verified by the standard error of the linear regression, which with a 95% confidence interval is $\pm 6.2\%$. This is the error which has been reported on the per capita roof area values. Further, many of the buildings (rural and missed large, flat and grey buildings) were outlined by hand and therefore constitute an error much lower than 15%.

As discussed in Section 3.2, the accuracy of the FA process is highly dependent on the similarity of the building typology under analysis to that in the orthophoto used as a training set to create the AFE. In this case, the AFE was developed for an older, mature neighbourhood, which represented the majority of the Kingston area. As a result, it was less accurate when applied to the newer suburban areas on the other side of the city. A similar discrepancy will have been encountered in each of the CSD analyses.

The focus of this paper is on the extraction of roof area for PV analysis; the calculation of PV potential itself may be tailored by other researchers to specific analyses based on projected panel distributions and efficiencies. Thus, a basic approach has been taken to estimate PV power and energy potentials in the large-scale RER in this analysis. It should be kept in mind that there is an additional error associated with this aspect of the analysis.

5. Discussion and Policy Implications

The potential output from the deployment of rooftop PV in the RER showcases the important influence that these technologies can have on the large-scale electrical system. To understand the effect of rooftop PV deployment, the power and energy outputs are compared to the demands in Ontario as a whole and the RER specifically.

As seen in Table 4, if PV models from the high efficiency range of the current panels on the market are utilized, based on the demands seen in 2008 (IESO, 2009; IESO, n.d.), rooftop solar photovoltaics can provide 24% of the peak Ontario power demand, or approximately 157% of the peak demand in the south eastern region (power output from equation (6); power demands from IESO, 2009 with RER assumed to be East and Ottawa zones). Further, five per cent of total annual energy use of Ontario can be supplied (energy output from equation (7); energy demands from IESO, n.d.). Recall that this five per cent is generated by rooftops in the RER, which is inhabited by only 16% of Ontario's population (StatsCan, 2009). Since it has been shown that roof area has a generally constant relationship with population, it may be inferred that there is much more energy potential across the entire province. In fact, if the roof area-population relationship found in the RER can be shown in the future to hold throughout all of

Ontario, then as high as 30% of Ontario's annual energy demands could potentially be supplied by rooftop PV alone. This has an immense significance to energy policy formulation, particularly in urban areas. These results indicate that the FIT has the potential to initiate considerable renewable power inputs to the Ontario grid from roof-mounted PV alone.

The use of solar photovoltaic technologies is complicated because of the temporal and seasonal nature of solar irradiation. For example, while rooftop PV has the potential to supply 157% of the peak power demand in the RER, without storage this is only possible if the peak hours of the sun correspond with the instance of peak demand. Further, the energy supply from rooftop PV will not supply a constant 5% of Ontario's annual energy demand; rather, it will supply more than this during the summer months, and less during the winter. Fortunately, however, the times of highest power demand (summer air conditioning peaks) tend to correspond to the times of highest solar flux (Pearce, 2009; Perez & Collins, 2004). Through innovation and careful policy choices, these unique features of solar energy availability may be mitigated, and even capitalized upon.

A first policy measure to explore with relation to PV, therefore, is energy storage, which is critical in times when power demands do not match PV power generation. Energy storage allows for increased capacity and flexibility of the system, making it possible to achieve increased PV penetration rates (Denholm & Margolis, 2007). Options for storage include compressed-air, hydraulic pumping, flywheels and many types of battery technologies (Nourai, 2005). Storage is felt to be a key aspect in better grid performance and financial gains (Brandon, 2008; Denholm & Margolis, 2007; Nourai, 2005).

A second initiative to consider is the coupling of PV with other energy technologies. Hybrid combined heat and power (CHP)-PV systems enable CHP to provide back up for the intermittent nature of the solar resource (Pearce, 2009; Derewonko and Pearce, 2009). CHP systems are significantly more efficient than conventional power systems because of their ability to use thermal energy which is typically released as waste heat (Pearce, 2009; Siddiqui et al., 2003). Although the addition of CHP is more complicated physically, the energy and economic savings can be considerable particularly when CHP systems are installed near to a heat sink (Siddiqui et al., 2003), as in a household where there are several thermal demands, such as water and space heating, for example.

The design of the electric grid is another major policy consideration in the large-scale deployment of PV. Because of the distributed nature of PV, particularly that of mass deployment of rooftop solar, significant changes in grid capabilities will be required. The facilitation of distributed generation (DG), in contrast to conventional vertical supply systems, should be a strong consideration in future grid upgrades – this is an important factor in the future of the Ontario electricity system (Shalaby, 2008).

A final policy aspect in the large-scale deployment of rooftop PV technologies in the RER is the consideration of which locations should be prioritized for deployment. The capacity of the existing grid to receive additional power is a primary consideration. Additionally, an important finding of this paper is that across the region as a whole, roof area generally is constant as a function of population (although roof area per capita shows an increase in the less densely populated regions). This indicates that the more rural regions offer a particularly large opportunity for rooftop PV deployment, especially given their higher transmission costs on the conventional grid system. However, the large-scale deployment of rooftop PV holds great potential across all areas of the RER, and therefore also across Ontario and the country.

6. Future Work

Throughout this paper, a number of opportunities for future works have surfaced that can serve to expand and solidify the discoveries made here. First, the collection of more roof area-population data points across Ontario and the country will help to confirm the relationships explored in this research. The completion of the DRAPE orthophoto project, and other similar imagery projects, is an important step in making this methodology usable elsewhere. Available data is a crucial part of this type of analysis. Municipalities, cities and towns should be encouraged to compile roof print data of their own; as has been mentioned, this is important for informing beneficial environmental policy surrounding more than PV. Further, a careful analysis of trends in building orientation, shading and other uses in the Ontarian context should be conducted in order to increase the accuracy of the conversion factors used to convert total roof area to PV-available roof area. Additionally, more refined energy modeling taking into consideration of solar panel tilt and azimuth angles could be made. Finally, a more in-depth analysis of the ability of rooftop solar to meet peak and overall power and energy demands could be carried out, accounting for the temporal and seasonal nature of solar energy and the variable distribution of insolation across the region.

In the future, the findings described here will be consolidated by the Queen's Institute for Energy and Environment Policy with research concerning other renewable energy opportunities for the region. This work will inform the ways in which south eastern Ontario can move toward truly being a "Renewable Energy Region" and thus a net generator of renewable energy.

7. Conclusions

This paper has used geographic information systems and advanced feature extraction algorithms to deepen the understanding of building form and distribution in a specific "Renewable Energy Region" of south eastern Ontario for the purpose of quantifying potential for rooftop solar photovoltaic (PV) deployment. A five-step procedure has been developed for estimating total rooftop PV potential which involves geographical division of the region; sampling using the Feature Analyst extraction software; extrapolation using roof area-population relationships; reduction for shading, other uses and orientation; and conversion to power and energy outputs. The methodology consists of a broad set of principles and techniques which may be used and modified conveniently in other related initiatives to forward knowledge concerning PV potential in general.

This research has investigated the use of Feature Analyst in large-scale rooftop analyses, particularly in the study of PV potential. It has also explored the relationship between roof area and population and has discovered a constant total roof area of 70.0 m²/capita \pm 6.2% which applies across the region as a whole. With reference to similar numbers found in other parts of the world, this value demonstrates the low-density character of Canadian settlements and the relative abundance of roof area possessed here. This understanding is critical to determining potential PV deployment in this region, but is also highly important to many other fields, allowing for the better informing of policy surrounding other applied sustainability initiatives such stormwater runoff, green roof deployment, solar thermal applications and land-use planning in general.

Potential peak power outputs for the region with roof tops covered with PV range from 2.05-5.74 GW, depending on the panel efficiencies used. Potential annual energy production ranges from 2474-6909 GWh. These outputs are considerable; based on the higher efficiency PV panels, rooftop PV deployment in the region could supply 24% of Ontario's or 157% of the region's peak power demands, based on 2008 figures. In terms of energy, 5% of Ontario's total annual demand can be met with only rooftops in the region of study, suggesting potentially 30% of Ontario's energy demand can be met with province-wide rooftop deployment.

These results confirm that the Ontario Feed-In Tariff has the potential to initiate significant renewable energy inputs to the Ontario grid. This new understanding of roof area distribution and potential PV outputs has an immense significance to policy formulation in the region: there should be a shift toward establishing solar photovoltaics as a major policy focus in the region, and across Canada, in the move toward a sustainable future.

Acknowledgements

The authors would like to acknowledge helpful discussions and suggestions from T. Carpenter, W. Mabee, G. McQuat, S. Keating, E. Shackles, R. Kenny, C. Law, and the anonymous reviewers. Funding for this project was provided by the Queen's Institute for

Published in: L.K. Wiginton, H. T. Nguyen, J.M. Pearce, "Quantifying Solar Photovoltaic Potential on a Large Scale for Renewable Energy Regional Policy", *Computers, Environment and Urban Systems* 34, (2010) pp. 345-357.
<http://dx.doi.org/10.1016/j.compenvurbsys.2010.01.001>

Energy and Environmental Policy and the Natural Sciences and Engineering Research Council of Canada. The authors would also like to acknowledge the assistance of S. Greaves at the Maps, Data and Government Information Library at Queen's University and the Ministry of Natural Resources in Peterborough, Ontario.

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Glossary

AFE: automated feature extraction

CSD: census subdivisions

DRAPE: Digital Raster Acquisition Project – East

FA: Feature Analyst

FIT: feed in tariff

GHGs: green house gases

NAD83: North American Datum 1983

OEEDC: Ontario East Economic Development Commission

orthophoto: an aerial photograph geometrically corrected ('orthorectified') such that the scale is uniform

PV: photovoltaic

QIEEP: Queen’s Institute of Energy and Environmental Policy

RER: Renewable Energy Region

shapefile: simple GIS vector files containing points, lines or areas.

UTM: Universal Transverse Mercator

Captions (Figures)

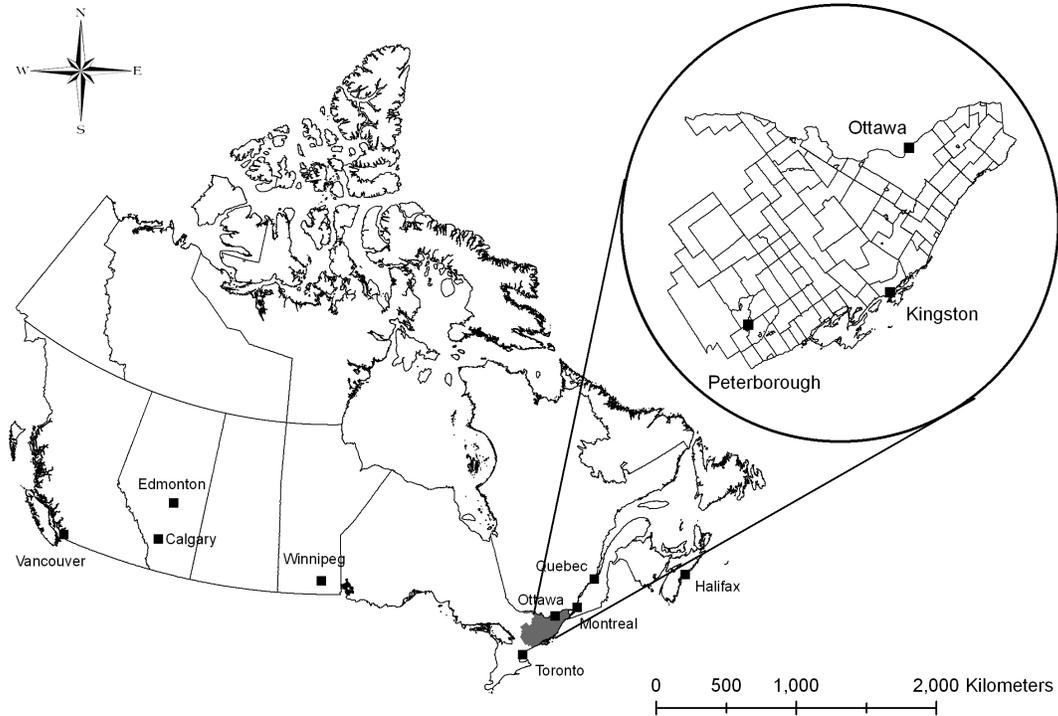


Figure 1
Map of Canada, inset shows the Renewable Energy Region in southeastern Ontario

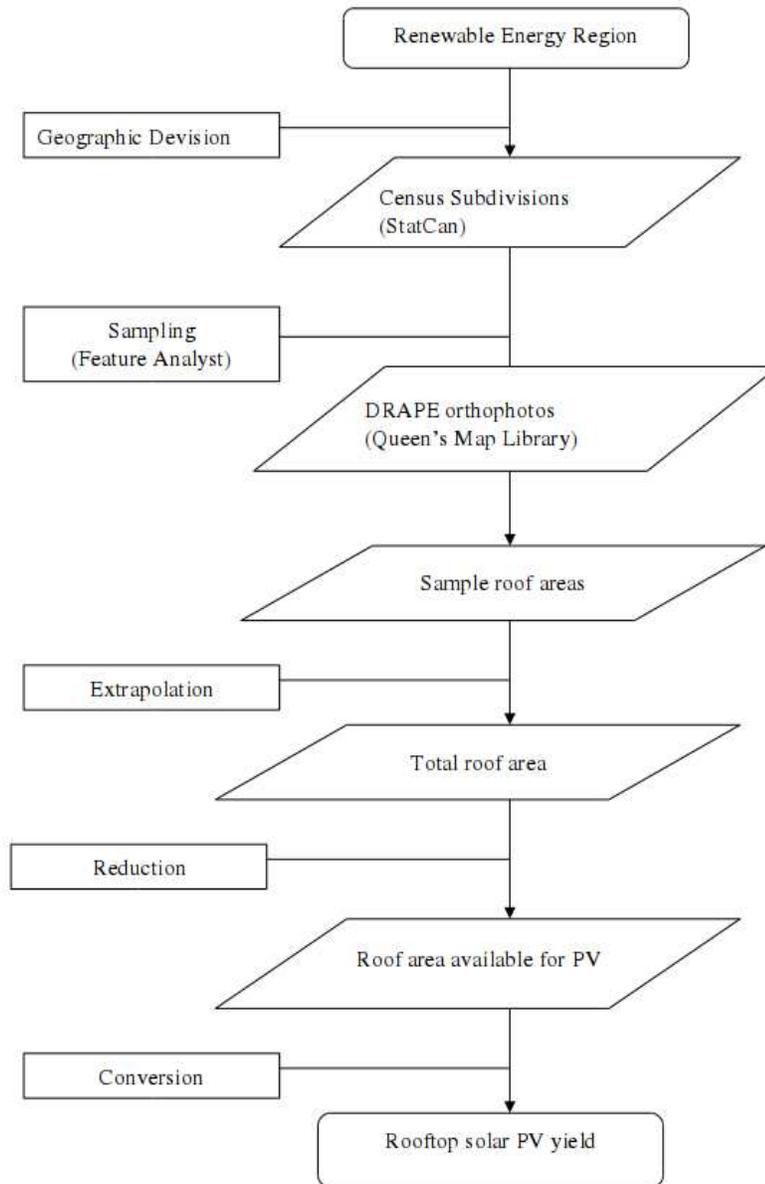


Figure 2
Overall workflow for determining roof area available for solar PV in a large-scale region

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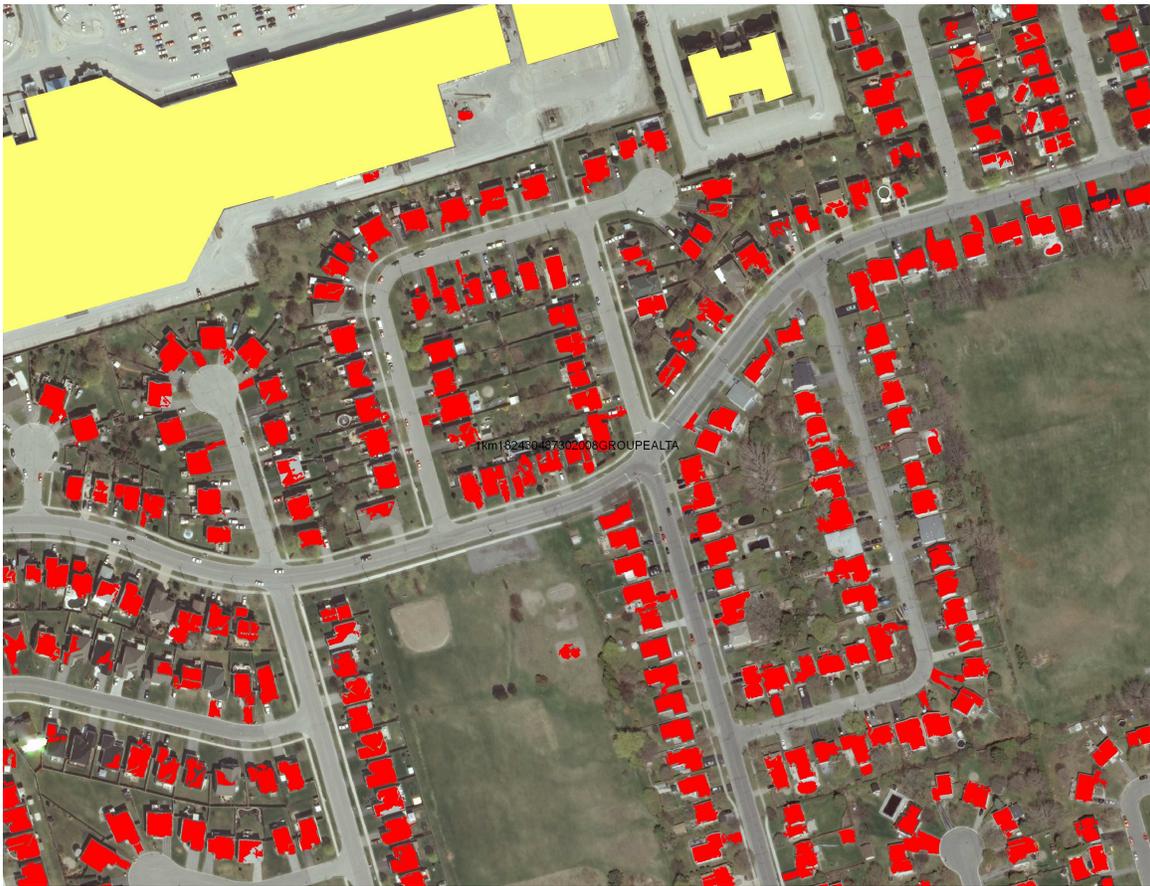


Figure 5
Sample automated feature extraction results

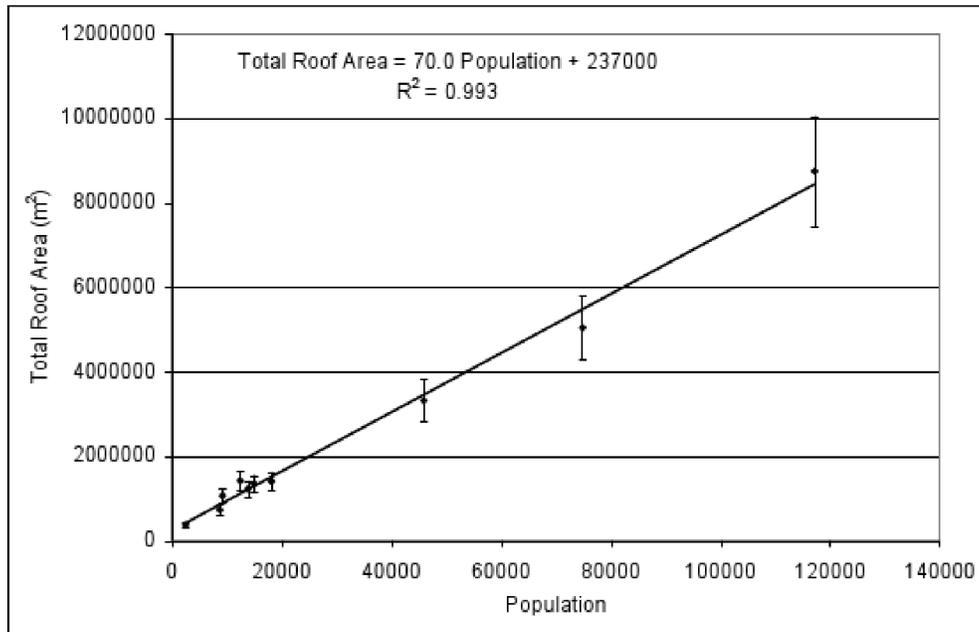


Figure 6
Total roof area as a function of population in the Renewable Energy Region
Footnote: Error bars represent a conservative 15% error on each data point as discussed in Section 4.4.

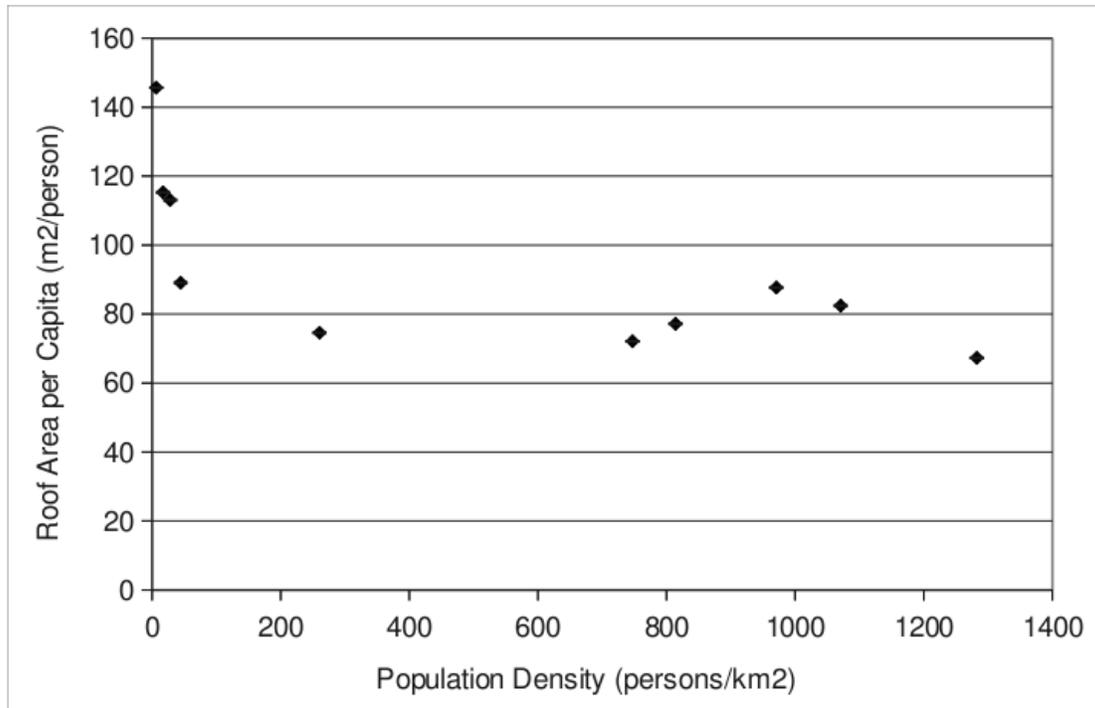


Figure 7
Total roof area per capita decreases with increasing population density

able 1 - Representative characteristics of sampled census subdivisions

Census Subdivision (CSD)	Population Density (persons/km²)	Population Density Classification	Settlement Typology
Cobourg	814.0	High	Residential, commercial, institutions
Cornwall	747.1	High	Residential, highly industrial
Killaloe, Hagarty and Richards	6.4	Low	Rural residential, sheds and barns, open space and forest
Kingston	260.2	Medium	Residential, commercial, institutions
Laurentian Valley	16.8	Low	Rural residential, sheds and barns, open space and forest
Loyalist	44.3	Low	Rural residential, agriculture and forest
Pembroke	970.7	High	Residential, some industry
Peterborough	1282.6	High	Residential, commercial, institutions
Smiths Falls	1070.7	High	Residential, some industry
South Stormont	28.0	Low	Rural residential, highly agricultural

Table 2 - Fraction of available roof area for solar PV application from five research initiatives

Location	Building Type Assessed	Criteria Used	Method	Fraction of Available Roof Area	Reference
Spain	All buildings within urban-designated areas	Accounts for shading and other roof uses	Human inspection	0.34	Izquierdo et al., 2008
Germany, Western Europe	Segments of buildings which have been designated as “solar appropriate”	Accounts for shading and other roof uses	Estimation	0.90	Lehmann & Peter, 2003
Switzerland	Three urban sites	Irradiation, daylight fluxes, polar diagrams, sky view factors	Computer ray-tracing simulations	0.95 0.73 0.49	Scartezzini et al., 2002; Montavon et al., 2004
India	Houses, hospitals, hotels and nursing homes	Accounts for shading and other roof uses	Estimation	0.30	Pillai & Banerjee, 2007
New Zealand	Five residential blocks	Fraction of roof area within 45 degrees to north	CITYgreen GIS software	0.30 0.23 0.30 0.22 0.47	Ghosh & Vale, 2006

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Table 3 - Power and energy outputs in Renewable Energy Region based on four PV panel scenarios

Solar PV Panel Type	Module Efficiency	Panel Output (W/m²)	Power Output Per Capita (kW/cap)	Power Output for RER (GW)	Annual Energy Produced Per Capita (kWh/cap)	Annual Energy Produced for RER (GWh)
Si (crystalline)	22.9%	229	3.01	5.74	3620	6909
Si (multicrystalline)	15.5 %	155	2.03	3.88	2450	4676
a-Si/a-SiGe/a-SiGe (multijunction)	10.4%	104	1.37	3.61	1644	3138
Si (thin-film polycrystalline)	8.2%	82	1.08	2.05	1296	2474
Efficiencies from M.A. Green et al. (2009) calculated using global AM1.5 spectrum = 1000 W/m ² ; mean daily global insolation with horizontal tilt (annual mean) from Natural Resources Canada, insolation = 3.3 kWh/ m ² .						

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Table 4 - Ability of rooftop solar PV to meet provincial and regional power and energy demands

Solar PV Panel Type	Percentage of Ontario Peak Power Demand [24.2 GW]	Percentage of RER Peak Power Demand [3.7 GW]	Percentage of Ontario Annual Energy Use [148 000 GWh]
Si (crystalline)	24%	157%	5%
Si (multicrystalline)	16%	105%	3%
a-Si/a-SiGe/a-SiGe (tandem)	11%	71%	2%
Si (thin-film polycrystalline)	8%	56%	2%
Sources: Power demand from IESO, 2009 and energy demand from IESO, n.d.			