MULTI-SCALE MODELLING OF POTENTIAL SOLAR POWER GENERATION IN URBAN AREAS

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Decentralized power generation through photovoltaics (PVs) is widely regarded as contributing favorably to environmental, economic, and social aspects of urban sustainability. The optimized use of decentralized solar PV power generation, however, requires estimation of the potential for building surfaces and their electricity demand, as well as the design of smart distribution systems and transmission grids. Here we propose methods to estimate the solar PV power generation in urban areas in an efficient way. The methods apply to individual buildings, neighborhoods, cities as well as entire countries. Our results show that GIS and LiDAR point data-based methods are promising approaches for estimating the solar PV power generation on building roofs and facades at the scales from individual buildings to cities. LiDAR methods are, however, difficult to apply to entire countries (national scale), in which case Machine-Learning methods are more appropriate. Generally, whenever massive amount of data are available, as for whole countries, Machine-Learning methods are a good alternative to LiDAR-based methods for the estimation of solar PV power generation on building roofs and facades.

Rooftop photovoltaics, spatio-temporal mapping, solar-power generation, cities

I. INTRODUCTION

Distributed power generation through photovoltaics (PVs) is generally regarded as contributing favourably to environmental, economic, and social aspects of urban sustainability. Considerable part of the solar PV power generation in the future is likely to be urban-based. This is partly because cities provide large areas, namely rooftops and facades as well as street/highway surfaces, for PV installations. Cumulatively, these areas are very extensive – and large areas are needed to make solar energy the main electricity source - and mostly not used for other purposes. The optimized use of decentralized solar PV power generation, however, requires the estimation of the potential on building rooftops and facades, the electricity demand values, as well as the design of smart distribution systems and transmission grids. While the estimation of the potential for solar PV power generation, from that of individual buildings to entire cities and countries, is essential for the grid integration, it is a complex process that requires rigorous methods. There have been many studies in recent years that have estimated the photovoltaic solar power-generation potential from the scale of individual buildings and neighbourhoods (local scale), to the scales of entire cities and countries (national scale) [1-8]. Methods used for estimating the potential of PV power generation are different and depend on the availability of data, the aim and scale of the study, and the spatial/geographical characteristics. The methods include (i) simulation methods, (ii) sampling techniques, (iii) GIS-based Feature Analyst (FA) tools, (iv) statistical methods, (v) aerial images, (vi) ArcGIS together with LiDAR (Light Detection and Ranging) data, and recently (vii) machine-learning methods. The man aim of the present article is to discuss the cons and pros of each method for different scale of study and their efficiency. In addition, we propose novel approaches for each scale and show how the modelling tools have been used to estimate the solar PV power generation at building and neighbourhood scale, as well as city and national scale, in Switzerland.

II. DATA AND METHODS

For building, neighbourhood and city scale estimation of PV power generation we use the city of Geneva in Switzerland as a case study. The city is situated in the southwestern part of Switzerland; more specifically at 46°12'N and 6°09' E. Bounded to the northeast by Lake Geneva, where the lake flows back into the river Rhône, Geneva is surrounded by two mountain chains, that is, the Alps and the Jura. The average height of above sea level is 374 m. Its population is about 195 thousand (www.bfs.admin.ch). It is thus the second largest city in Switzerland (after Zürich). For the national scale we use the entire Switzerland as the main case study. Switzerland is located in the centre of Western Europe, at latitude 46° 57′ N and longitude 7° 27′ E, and has an area of 41,285 km^2. Nearly two-thirds of its territory is mountains (the Swiss Alps and the Jura Mountains), which creates a significant variation in climate between the north and south parts of the country. In this study, we use the communes (the smallest administrative divisions) and a grid size of 200m × 200m as the two aggregation level for

presenting the rooftop solar PV power generation results.

A. Modelling Solar PV Power Generation at Building and Neighbourhood Scale

High resolution urban LiDAR point data which is freely available for the city of Geneva and can be collected from

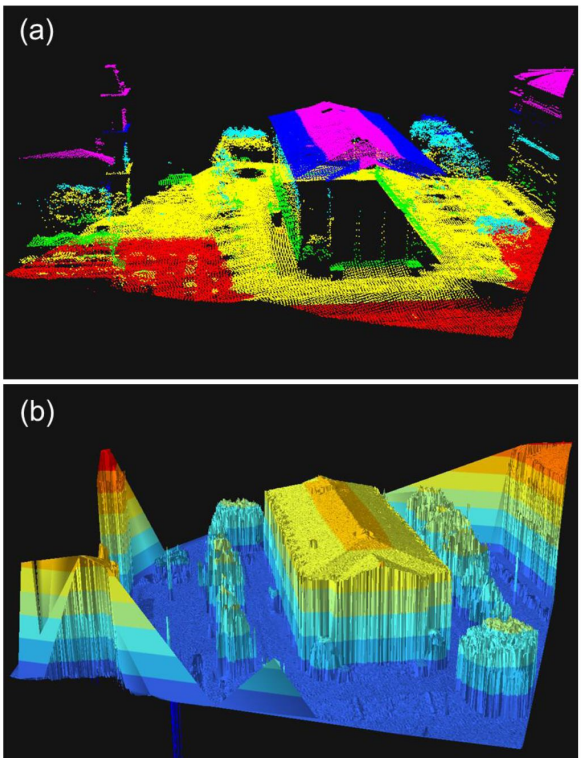


Fig. 1. Visualisation of LiDAR data (a) as points, (b) as triangulated surfaces. The variation in colours shows the differences in elevation values for points and surfaces.

Le système d'information du territoire à Genève (http://ge.ch/sitg/) is used. The LiDAR point data for Geneva was created in 2013 and has the following characteristics: Average point density is 15 points/m^2, vertical precision is ±10cm, and horizontal precision is ±20cm. While these data points represent precisely the urban form (building geometry, trees and landscape), they have some limitations. For example, there are almost no points with the same X and Y coordinates, which makes it difficult to map precisely any vertical features like building facades. The visualisation of LiDAR point data for one building and its surroundings is presented in Fig. 1. Weather conditions have large impact on the results of modelling of the solar irradiation. We use hourly measured weather data from Meteonorm which includes direct and diffuse solar irradiation on horizontal surfaces. Instead of having weather data for one specific year, in order to be more accurate we use historical weather data. The data presents averaged irradiation data for the years 1991 to 2010. While the historical weather data are quite useful for monthly and yearly solar irradiation estimations, for short-term variability (e.g. hourly estimation) it is better to use a statistical model (e.g. Markov chain) to predict the hourly irradiation values based on historical weather data. In this study, however, we use the averaged weather data from Meteonorm.

Below we briefly explain in different steps how the algorithm for spatio-temporal solar irradiation modelling using LiDAR point data has been developed. More details are given in [9]. The algorithm computes solar irradiation simultaneously for roof, ground and facade surfaces of buildings. The algorithm is then implemented and tested inside the Matlab environment. The intermediate and final results are visualized either using Matlab or exported as shapefile in ArcScene. The steps are as follows [9]: (1) Elevation raster computation. (2) Extrapolation of elevation raster to a regular 3D grid. This includes to (i) compute slope and aspect values for each point, (ii) create hyperpoints where the slope value for each point is larger than 72 degrees, (iii) improve facade model including (a) remove redundant hyperpoints and (b) adjust height of hyperpoints, (iv) remediate high slope values close to facades. (3) Solar irradiation matrix computation. This includes (i) computation of the sun position for every hour in the considered time interval, (ii) transformation of direct horizontal irradiation to direct irradiation on an inclined plane for every combination of slope and aspect values for every hour in the considered time frame, and (c) transformation of diffusive horizontal irradiation to diffusive irradiation on inclined plane for every combination of slope and aspect values for every hour in the considered time frame. (4) Shadow algorithm / viewshed computation. (5) Direct and diffusive irradiation on every point.

B. Modelling Solar PV Power Generation at City Scale

Yearly and monthly mean solar radiation for the rooftops of more than 10,000 buildings (city scale) have been estimated using fine resolution LiDAR point data. We used solar radiation analysis tools in Geographic Information System (GIS), in combination with MATLAB, to model solar PV power generation on building rooftops [10]. Deploying a Digital Surface Model (DSM) with precision of 0.5m × 0.5m, the results were obtained in the following steps: (1) viewshed calculations (to determine what part of the sky is visible from each cell in the raster map); (2) sun-map calculations (to compute the direct radiation); (3) sky-map calculations (to compute diffuse radiation); (4) overlay of viewshed with the sun map and the sky map; and (5) summing up the direct and diffuse radiations to estimate the global solar radiation. The energy output, that is, the maximum potential of solar PV power generation on the rooftops is estimated through multiplying the annual mean solar radiation (GWh/year) and the useful roof area for PV installation, taking into account the average efficiency (20%) and the 79% performance ratio for mono-crystalline PV panels. In order to fit our model

with the meteorological data, the parameters Transmittivity (the fraction of radiation that passes through the atmosphere, averaged over all wavelengths) and Diffusive Proportion must be modified from their default values in ArcGIS - which are normally for the clear-sky conditions. We used monthly average cloud-cover data (percentage) from Meteonorm in order to assign the percentages for each month of a typical year for Transmittivity and Diffusive Proportion. Also, the azimuth and zenith divisions (the number of divisions used to create sky sectors in the sky map) has been modified from their default values and set at 16 azimuth and 16 zenith divisions (the default value is 8 divisions). Similarly, in ArcGIS the default number of azimuth directions used when calculating the view shed is 32, while we used 64. Also, the default resolution or sky size for the view shed, sky map, and skyp map rasters uses 200 × 200 cells whereas we used a raster of 400 × 400 cells.

CitySim is used to simulate the hourly solar radiation and associated PV power generation for the rooftops and facades of all the buildings in the city of Geneva [11]. The hourly solar radiation on each of the building surfaces is based on simplified building roof geometry in that all the roofs are regarded as flat so as to decrease the computation time. Hourly solar radiation simulations for 8760 hour in a typical year were made for all the buildings. In CitySim [12] the simplified radiosity algorithm was used to calculate the incoming shortwave radiation on building surfaces including the inter-reflections. The weather data for one year period used in this simulation was obtained from Meteonorm (www.meteonorm.com) and consists of hourly values for air temperature, wind speed and direction, humidity, precipitation, diffuse horizontal irradiance, and beam normal irradiance. The solar radiation model in CitySim solves for beam (direct), diffuse and reflected irradiance using complex modelling techniques based on the Perez all-weather model [35] and simplified radiosity algorithm [32] for inter-reflections. This radiation model has been validated by inter-model comparison with RADIANCE [32].

C. Modelling Solar PV Power Generation National Scale

A machine-learning method was developed to estimate the solar PV power generation for building rooftops at the national scale for Switzerland [13-15]. Two most common algorithms, namely Support Vector Machines (SVM being part of the general family of kernel methods), and Random Forests (RF being part of the general family of ensemble learning methods) are used to do the estimation at two different resolutions: solar PV power generations of (i) 1900 communes/cities in the whole of Switzerland and (ii) a grid of 200m × 200m covering the entire Switzerland. Using the above algorithms, a hierarchical approach consistsing of three steps is used, namely: (i) The physical potential, which represents the total energy received from the sun by urban areas, (ii) the geographic or urban potential, which reflects the constraints on the locations where the solar energy can be captured and used for PV installations, and (iii) the technical potential, which translates into the final electrical energy output obtained from the system, using the technical characteristics of the PV technology.

III. RESULTS AND DISCUSSIONS

At building and neighborhood scale, the models for the annual, monthly, daily, and hourly solar irradiation on roofs, facades, and ground surface and the annual results are presented in Fig. [2]. The values for annual solar irradiation on roofs, façades, and ground-surfaces vary from 3 to 1524 kWh/m^2. Values for points located on the lower parts of facades are generally very low since they receive almost no direct and only very little diffusive irradiation, particularly the dense urban areas. The values computed for upper parts of south-east to south-west facing facades are as high as 700kWh/m^2/year in the dense areas and up to 1000kWh/m2/year for the less dense areas. The irradiation values on most roof points are computed between 900kWh/m^2/year and 1300kWh/m^2/year. The Fig. 2. (a) Annual solar irradiation (kWh/m2) using LiDAR point data. (b) Daily solar irradiation (kWh/m2) profile for roof and façade.
two different points located on the roof and facade of a building have been generated in Fig. [2]. The developed 3D solar algorithm is more efficient and has several advantages over the algorithm implemented for 2D solar raster computation in ArcGIS: (a) High slope values close to facades are corrected before solar irradiation is computed, (b) the possibility of using measured weather data, (c) the possibility of using an anisotropic model instead of an isotropic model for diffuse irradiation, and (d) more accurate computation of solar irradiation values on an hourly bases for power generation and integrated with the data from the grid. In addition, the developed algorithm based on LiDAR point data has several advantages over the vector–based solar models: (a) no need to produce building geometry in advance, (b) in vector-based models many obstacles including vegetation are missing, which can have an important impact on the estimation of irradiation values for facades, (c) The LiDAR point data is often freely available for public and with the proposed algorithm even people with little knowledge can easily produce 3D solar irradiation maps for preliminary studies.

At a city scale, we used solar radiation analysis tools in Geographic Information System (GIS), in combination with MATLAB, to model yearly and monthly solar PV power generation on building roofs. Fig. 3 is a

visualization of the solar potential availability on the rooftops at city scale. We also use another simulation tool, namely CitySim, to compute the hourly solar PV power generations for the building roofs and facades. CitySim, a software has been developed at Solar Energy and Building Physics Laboratory at EPFL, uses a vector-building data to simulate the solar irradiations on building envelope including facades [6,7]. While it does takes into account the physical characteristics of buildings and neighboring buildings, it would be computationally very demanding to include the topography, urban landscape, and surrounding environment.

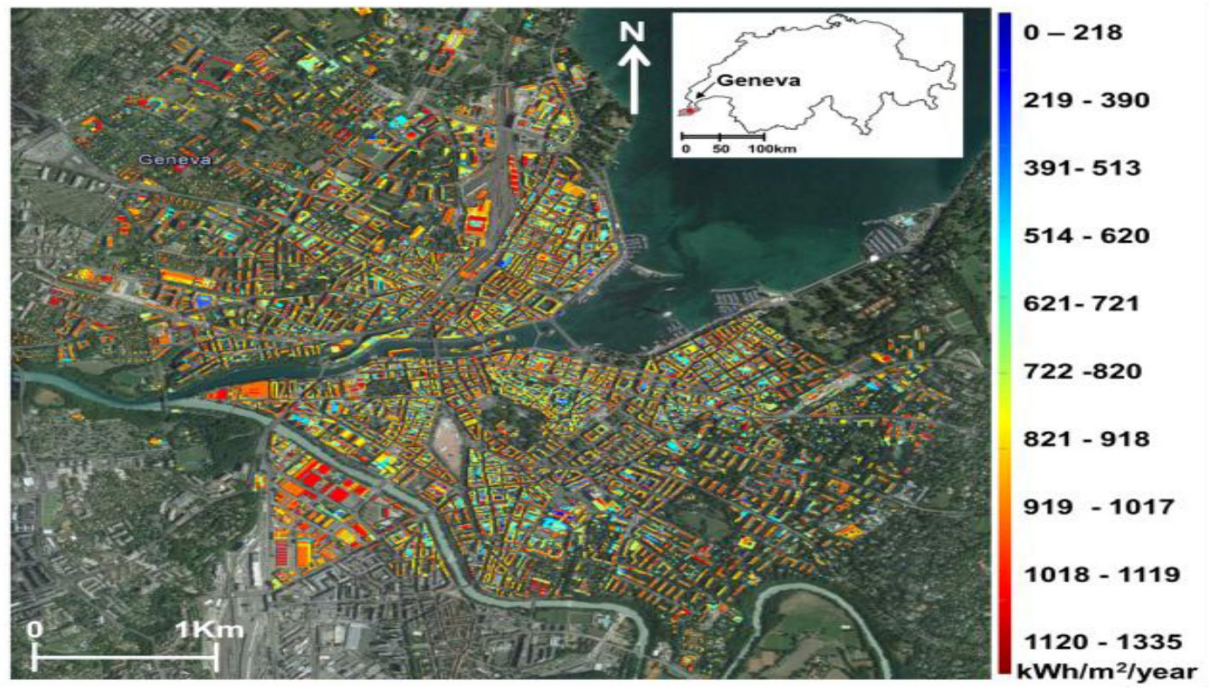


Fig. 3. Yearly mean solar radiation received by building roofs in the city of Geneva.

For the national scale, the use of machine-learning algorithms is a promising step towards accurate estimation of technical potential of rooftop PV power generation in Switzerland Fig. [4]. Our study shows that the annual PV electricity production in Switzerland for the urban areas in its 1901 cities is 17.86 TWh (assuming 80% performance ratio and 17% efficiency). The total domestic electricity consumption in 2015 (including losses occurring in transmission and distribution) in Switzerland was 62.6 TWh (http://www.bfe.admin.ch/).



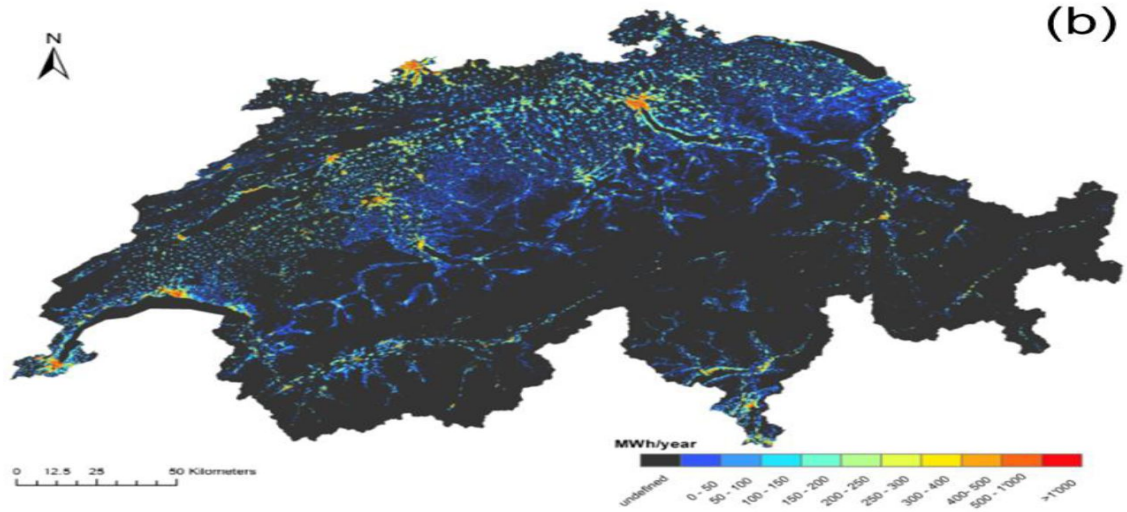


Fig. 4. Technical potential of rooftop PV power generation (GWh/year) for each of the 1901 cities in Switzerland (a), and for each pixel in the size of 200m x 200m (b).

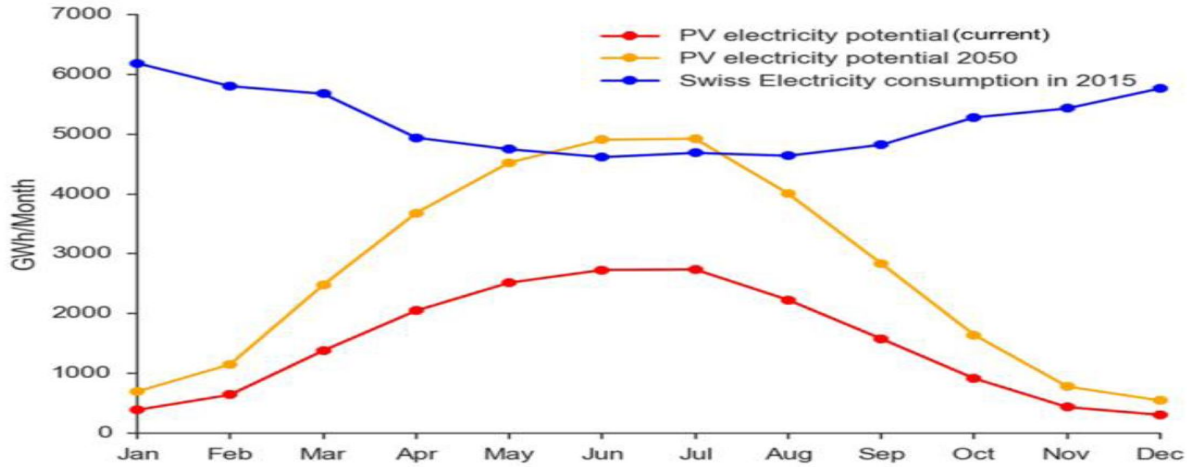


Fig. 5. Comparison between current and forecasted monthly PV power generation (GWh/month) for the 1901 cities in Switzerland (current year marked in red; year 2050 marked in orange), and Swiss electricity consumption in 2015 in GWh/month (marked in blue).

The estimated PV electricity production from buildings in urban areas can provide 28% of annual electricity consumption in Switzerland. While in the majority of cities the potential PV electricity production is less than 15 GWh/year, in a significant minority (about 15% of cities) the potential production may exceed 15 GWh/year. More specifically, these 15% of cities can potentially produce 53% of the total Swiss electricity use as of 2015. The values vary between different cities in Switzerland. More specifically, for Zurich the potential production is 574 GWh/year, for Basel 291 GWh/year, and for Bern 255 GWh/year. These are the top three cities for the potential PV electricity production in Switzerland. While only 1.2% of the total electricity generated in Switzerland in 2014 comes from PV, the production of electricity from PV is forecasted to increase to 13.4% by 2050. Assuming an annual increase in cell efficiency of the crystalline silicon wafers of 0.3% per year, the panel efficiency will increase to 27.2% by 2050, Fig. [5]. Our modelling results also show that Switzerland has a large PV rooftop potential that can provide a considerable share of the future electricity use in Switzerland. For large-scale deployment of rooftop PV, the design of the future electric grid, the significant changes in grid capabilities, the capacity of the existing grid to receive additional power, and the contribution of rural and urban areas for rooftop PV deployment in Swiss grid, should all be of primary consideration in future studies.

CONCLUSIONS

Our results show that GIS and LiDAR point-data-based methods are promising approaches for estimating the solar PV power generation potential on building roofs and facades from the scale of individual buildings to the scale of neighborhoods and entire cities. Considerable increase in the availability of high-resolution LiDAR data and improvements in technology and computational capability should increase the efficiency and accuracy of the modelling. These methods are particularly suitable for solar PV power generation modelling at the building to city

scales, but rather less so for large-scale modelling of entire countries. Whenever massive amount of data is available, Machine-Learning methods can be a good alternative to LiDAR-based methods for the national-scale estimations of solar PV power generation potential on building roofs and facades.

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