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A critical comparison of methods to estimate solar rooftop photovoltaic potential in Switzerland

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Abstract. To understand the opportunities and challenges of large shares of solar photovoltaics (PV) in our electricity mix, various large-scale studies of PV potential on building roofs have been conducted in recent years. The use of different datasets, methods and spatio-temporal resolutions leads to widely varying results, making a comparison across different studies intrinsically difficult. In this work, six studies carried out in Switzerland are compared in a quantitative way, in order to understand how different methods impact the potential estimates. We observe a strong trend towards increasing spatial and temporal resolutions, using larger and more accurate datasets for the analysis. While the earliest study relies on rules of thumb, later studies use data-driven estimations, enabled by the use of Machine Learning, scalable algorithms and powerful computational engines. Our analysis shows that the largest differences are caused by the source of the solar radiation input data, the computation of shading effects on rooftops and the estimation of available roof area for PV panel installation. The latter is the most uncertain parameter in the presented studies and offers opportunities for future work.

1. Introduction

Installing photovoltaics (PV) on building rooftops is a promising approach to reduce greenhouse gas emissions, especially in dense urban areas. Understanding the large-scale potential for rooftop PV is important for several reasons, including electricity network design, urban and regional energy planning, as well as incentive policies for PV installations. Several studies in recent years focus on assessing a large-scale technical rooftop PV potential. Early methods relying on “rules of thumb” [1] have been continuously improved by incorporating environmental and building data as well as using powerful computational engines and advanced analytic methods such as Machine Learning (ML). This progress in data processing, enabled by the availability of larger and more accurate datasets, has led to widely varying results of PV potential studies, even for the same geographic area. This makes the comparison across studies intrinsically challenging. Assouline *et al.* [2] provide an overview of the existing methods to estimate a large-scale technical rooftop PV potential, however this methodological review does not discuss the results obtained by individual studies. Some of these compare their results with those of other studies, but the discrepancies are explained in a qualitative rather than quantitative way [3,4].

In this paper, we propose a framework to compare large-scale rooftop PV assessment studies in a quantitative way. This helps us to understand how different methods impact the potential estimates. We focus our comparison on Switzerland, where six different studies have been carried out at national scale



from 2002 to 2019 [1,3–7]. The results are interpreted with respect to the following aspects: (i) target audience, (ii) spatio-temporal resolution, (iii) datasets, and (iv) methods. We finally provide a perspective on future developments which may further improve the PV potential studies. In Switzerland, the following six studies have been conducted at different scales.

1. The first study (S1) was conducted for several European countries including Switzerland by the International Energy Agency (IEA) in 2002 [1]. The method is based on rules of thumb, established at European scale, and does not reflect the local building stock characteristics within Switzerland. The technical potential is given as a yearly value for the entire country, representing the lowest temporal and spatial resolution among the compared studies. It is aimed at indicating an order of magnitude of the total technical rooftop PV potential at national scale.
2. The second study (S2) for Switzerland was conducted by Assouline *et al.* [3] at commune scale. In this study, a Machine Learning algorithm, Support Vector Machines (SVM), combined with Geographic Information Systems (GIS), is used in order to estimate the technical PV potential on building rooftops. ML is used as an effective method of extrapolation to solve problems of data availability in parts of the study area. The study is performed at monthly-mean-daily temporal resolution for all Swiss communes.
3. The third study (S3) is again conducted by Assouline *et al.* [4] at $200 \times 200 \text{ m}^2$ spatial resolution. In this study, another ML algorithm, Random Forests (RF), is used in combination with GIS to estimate the potential. The method from S3 is enhanced in S4 using (i) larger and more accurate datasets, (ii) a more efficient ML algorithm that includes the estimation of model uncertainties, and (iii) a higher spatial resolution of $200 \times 200 \text{ m}^2$. Both studies aim at a large-scale estimation of PV potential on building roofs to inform regional and national decision making.
4. The fourth study (S4) was conducted as a national project, namely Sonnendach.ch, by the Swiss Federal Offices of Energy (SFOE), Topography (Swisstopo), and Meteorology and Climatology (MeteoSwiss) [5,8]. Monthly solar PV potential is estimated for each rooftop in Switzerland using a GIS-based approach [5] complemented by rules of thumb [8]. In contrast to the above studies (S1-S3), the primary target group of this study is individual property owners and energy service providers interested in installing PV on specific building roofs. Thus, the primary output of this study is a classification of rooftop suitability for solar PV installation.
5. The fifth study (S5), conducted by Buffat *et al.* [6], estimates PV potential from solar radiation profiles in half-hour temporal resolution for pixels of $0.5 \times 0.5 \text{ m}^2$. In this study, GIS is used to estimate the solar radiation on tilted surfaces. In addition, the study includes a detailed model of the panel and inverter efficiencies. The results presented in the study aim primarily at a comparison between different PV technologies and are validated against measurement data.
6. The sixth study (S6) has been carried out by Walch *et al.* [7] based on a big data approach. In this study, Geographic Information Systems and Machine Learning approaches are used to estimate the solar PV potential for each building roof surface at hourly temporal resolution. ML is used to quantify not only the modelling uncertainty for the resulting PV potential estimation, but also the uncertainty in the data. The hourly temporal resolution of the results is very important for the spatio-temporal modelling of future electricity systems.

2. Methods and data

To compute the technical rooftop PV potential, a hierarchical approach has been widely accepted in the literature and is used in all studies. It includes (i) physical potential, that is, the amount of solar energy reaching the earth's surface, (ii) geographic potential, that is, the amount of solar radiation received by the tilted PV panels, which is affected by the geometry of the panel (slope and aspect), the shading from surrounding buildings and trees and the suitable area for the panel installation, and (iii) technical potential, that is, the maximum electricity output considering the technical characteristics of the PV technology (e.g. efficiency and system performance).

The physical potential is defined as the global horizontal solar radiation (G_h), consisting of a direct horizontal (G_B) and a diffuse horizontal (G_D) component. In S1, a constant G_h of $1,167 \text{ kWh/m}^2$ (from

Meteonorm) is used for the entire country. In all other studies (S2-S6), the three horizontal radiation components G_h , G_B and G_D are obtained from satellite-derived solar radiation data based on the Heliosat algorithm [9]. S2 and S3 use the mentioned data for 100 locations, S5 uses a gridded dataset at 3.8×5.6 km² spatial resolution (SARAH) and S4 and S6 use satellite data on a 1.6×2.3 km² grid provided by MeteoSwiss, which contains improvements for radiation modelling at high altitude [10]. S4 and S5 directly use the input data as physical potential. S2, S3 and S6 use Machine Learning to derive G_h , G_B and G_D on a 200×200 m² grid to better represent the local terrain. In S2 and S3, additional measurements of temperature, precipitation, sunshine duration and cloud cover are used to support the estimation, while S6 use exclusively spatial features, namely longitude, latitude and altitude.

The geographic potential is driven by two factors: (i) tilted radiation, that is, the solar radiation on a tilted PV panel (G_t , in kWh/m²) and (ii) available area for PV panel installation (A_{PV} , in m²). G_t and A_{PV} for a rooftop PV potential estimation may be generally defined as:

$$G_t = (1 - Sh_A) (Sh_{Bt} * G_{Bt} + SVF * G_{Dt} + G_{Rt}) \quad (1)$$

$$A_{PV} = A_{floor} * C_R \quad \forall A_{PV} > A_{min} \quad (2)$$

where G_{Bt} , G_{Dt} and G_{Rt} are the direct, diffuse and reflected tilted radiation components, Sh_A and Sh_{Bt} are parameters of shading losses, explained below, SVF denotes the sky view factor, A_{floor} is the ground floor area, C_R denotes the ratio of available area for PV panel installation over ground floor area and A_{min} describes the minimum roof area considered for PV installation. Despite following the same physical principles, differences in spatio-temporal resolution and available datasets lead to significantly varying methods for calculating the parameters for geographic potential, as summarized in table 1. It should be noted that probabilistic functions are used in S2 and S3 to compute the geographic potential as detailed roof shapes are unknown. One exception to equations (1) and (2) is S1, where the geographic potential is computed in a simplified way. In S1, G_t is obtained by multiplying G_h with an average solar yield ($\sim 93.3\%$ for Switzerland, derived from [1]). A_{PV} is computed by multiplying an estimated floor area (45m² per person) with the population size and a constant ratio of “architecturally suitable area / ground floor area”, equal to 0.72. This accounts for construction elements (here C_R) as well as shading (here Sh_A) [1].

In S2-S6, shading effects (Sh_A , Sh_{Bt}) are computed separately from C_R using GIS and a Digital Elevation Model (DEM). All studies use Switzerland’s DEM in 2×2 m² resolution, which was created by Swisstopo. S4 and S5 interpolate this DEM to a 0.5×0.5 m² resolution. We distinguish between two types of shading, namely (i) the fraction of a roof area in full shade (Sh_A), and (ii) the average amount of shading on the remaining roof (Sh_{Bt}), reducing the direct tilted radiation. Sh_A is only considered in S2, S3 and S6. S2 and S3 follow a Hillshade (HS) approach which estimates shading by computing relief maps for each pixel of a Digital Elevation Model (DEM). Sh_A is obtained from pixels with a HS value of 0, while Sh_{Bt} is obtained by averaging the remaining pixels over a building roof. ML is used by S2 and S3 to estimate shading effects at commune and pixel scale for Switzerland based on data from Geneva Canton. In contrast, S4-S6 use a horizon-based method, where binary maps of sun visibility are computed for each hour and each pixel of a DEM. S5 directly uses these binary maps to compute the per-pixel tilted radiation, so $Sh_{Bt} \in \{0, 1\}$. S4 and S6 average the results for each roof such that $Sh_{Bt} \in [0, 1]$. Sh_A is computed in S6 as areas with low sunlight exposure, i.e. $\overline{Sh_{Bt}} < 40\%$. SVF , which reduces the diffuse tilted radiation, is accounted for in S2 and S3 through a constant (0.9) and in S4 and S6 by using GIS. G_{Bt} , G_{Dt} and G_{Rt} are computed in S2 and S3 from daily solar radiation models [3,4]. S4-S6 use hourly models, explained in [11], and apply the anisotropic Perez model for the diffuse component.

The available roof area for PV panel installation is estimated in each study to a different extent. S5 does not compute any C_R , while S4 uses roof-specific rules of thumb based on expert knowledge, which are in the range of 0.42-0.8 [8]. S2, S3 and S6 use a combination of GIS and ML to obtain C_R . GIS is used in S2 to remove superstructures (SP) from roof polygons and to compute the resulting useful roof area. S3 improves on S2 by virtually installing PV panels (VP) on the building roofs. In both cases, the

GIS algorithms are applied to all rooftops in Geneva Canton, where detailed city GML data (LOD 4) is available. ML is then used to estimate C_R in all other communes/pixels based on building characteristics, which are derived from the Swiss building registry (RegBL). In contrast, S6 uses roof data for the entire country to virtually install panels, reducing the uncertainty related to estimating C_R with respect to S2 and S3. ML is applied in S6 to consider superstructures at national scale, by extrapolating the change in C_R when accounting for SP, which is again computed for Geneva Canton where LOD 4 data is available.

The technical potential is computed as shown in equation (3) by multiplying G_t , A_{PV} , the module efficiency (η) and a performance factor (PF), which accounts for losses of the inverter, soiling, degradation, etc. Most studies approximate η and PF using constants. S5 and S6 use physical models for module and inverter efficiencies. S5 further compares the results for monocrystalline, polycrystalline and thin film technologies. From an economic point of view, it is necessary to exclude unsuitable surfaces when estimating the solar rooftop PV potential. In S1, unsuitable surfaces are defined as those with a yield below 80%, which is approximated to be 55% of roofs [1]. S2, S3 and S6 define suitable roofs as those facing southwards, with an aspect angle of $\pm 90^\circ$ (east to west), while S4 and S5 exclude those roofs/pixels with an annual tilted radiation below 1,000 kWh (see table 1 for reference).

$$E_{PV} = G_t * A_{PV} * \eta * PF \quad \forall \text{ suitable roofs} \quad (3)$$

Table 1. Comparison of methods for computing the main parameters of rooftop PV potential.

Parameter	S1	S2	S3	S4	S5	S6
G_{Bt} , G_{Dt} , G_{Rt}	$G_h * yield$	Daily	Daily	Hourly	Hourly	Hourly
SVF	-	0.9	0.9	Horizon	1	0.9
Sh_{Bt}	-	Hillshade	Hillshade	Horizon	Horizon	Horizon
Sh_A	0.72	Hillshade = 0	Hillshade = 0	0	0	$\overline{Sh_{Bt}} < 40\%$
C_R	-	SP	SP + VP	0.42 – 0.8	1	SP + VP
A_{min}	-	28m ²	8m ²	10m ²	-	8m ²
Suitable roofs	55% of roofs	$roof\ aspect \in [-90^\circ, 90^\circ]$		$G_t > 1000 \text{ kWh/a}$		as S2/S3
η	10%	17%	17%	17%	Panel model	Panel model
PF		80%	80%	80%	Inverter model	Inverter model

Finally, the number of buildings considered in each study and the type of dataset used to describe buildings/roofs is important, as it impacts the total floor area (A_{floor}) and hence the order of magnitude of final PV potential. Again, S1 applies a rule of thumb of $A_{floor} = 45\text{m}^2$ per capita. S2 uses polygons of building clusters (Vector25) in urban areas only. S3 uses a combination of these building clusters and roof surface polygons with a higher spatial resolution, representing a total of nearly 2 million buildings in Switzerland [4]. The estimation in S5 is based on individual building footprints for the entire country, mostly from the Swiss cadastral survey. S4 and S6 use a national dataset of 9.6M roof surface polygons, representing 3.7M buildings, which was derived from a national 3D building model (LOD 2) by Swisstop³. It should be noted that the building footprint area in S5 is lower than the total building area declared by the Swiss Federal Statistical Office (2009 estimate) [6]. In contrast, the national roof surface dataset used in S3 (partly), S4 and S6 may overestimate total roof area, as some polygons overlap [12].

3. Metrics of comparison

The quantitative comparison of the studies, shown in table 2, is performed in terms of the main factors defined in equations (1)-(3) which can be derived from the results quoted in [1,3–7]. They include (i) ground floor area (A_{floor}), (ii) ratio of available roof area to ground floor area (C_R), (iii) available area for PV panel installation (A_{PV}), (iv) average national tilted radiation (G_t), (v) percentage of total roof area suitable for PV installation (*suitable roofs*, see table 1), (vi) system efficiency ($\eta_{sys} = \eta * PF$), (vii)

³ Detailed roof surface data for Switzerland were provided by the Swiss Federal Office of Energy.

annual estimated PV potential (E_{PV}) and (viii) PV potential normalized by roof surface area (\hat{E}_{PV}). As not all quantities are quoted in every study, some need to be derived from the given data. For this we use equation (3) together with some approximations that are specific to individual studies:

- a. In S1, only “solar architecturally suitable area” [1] is given as 138.2km², which combines *suitable roofs* and C_R . A_{PV} and A_{floor} are approximated by dividing by these factors, respectively.
- b. S2 and S3 do not state a percentage of *suitable roofs*, that is, a fraction of roof surfaces with a *roof aspect* $\in [-90^\circ, 90^\circ]$. This percentage is approximated based on the national roof surface dataset, in which 60.5% of roof area is facing southwards with *roof aspect* $\in [-90^\circ, 90^\circ]$.
- c. In S4, no national total PV potential is mentioned [5,8]. We thus aggregate the results for individual roofs, obtained by applying the method described in [8], to a national total.
- d. For S5, we derive the percentage of *suitable roofs* by dividing the suitable roof area (340km²), where $G_t > 1000\text{kWh/m}^2$, by the total ground floor area (485km²). G_t is obtained by dividing the total annual irradiation (400TWh) by the suitable roof area (340km²).
- e. S4 and S6 compute the PV potential per rooftop, based on a national dataset of building roofs. This dataset does not contain information on the floor area. A_{floor} is thus approximated as the total polygon area of all roof surfaces.

4. Results and Discussion

Table 2 shows the quantitative comparison between the different studies. A first noticeable difference is related to the ratio of available area for PV panel installation over ground floor area. The ratios used in S1 and S4 are comparable, indicating a rule of thumb for current installation practices. S2 and S3, which are based on data-driven methods that extrapolate C_R from Geneva Canton to the rest of the country, estimate higher ratios. In contrast, S6 quote a significantly lower value for C_R . As S6 is the only study which uses a GIS algorithm at national scale to obtain C_R , it is likely that earlier methods overestimated the ratio of available roof area to ground floor area. However, S3 and S6 also show that the estimation of the available roof area is highly uncertain. “Big data” can bring future improvements to reduce this uncertainty, e.g. through an image-based classification of superstructures. The percentage of suitable roofs, on the other hand, is comparable across studies. In general, we can see that assessing suitability by a minimum radiation threshold of 1000kWh/m² leads to approximately 10% more suitable roof surface area than using south-facing surfaces with a roof aspect below 90°.

The annual mean tilted radiation (G_t) ranges from 662 to 1,243kWh/m². The lowest values are found in S2 and S3, which use a conservative Hillshade analysis rather than the more optimistic Horizon method for computing shading. The highest values for G_t are found in S4 to S6, which follow similar approaches for the computation of the shading and tilted radiation components. These studies all use satellite data for the horizontal solar radiation. This is a strong indication that the choice of satellite or station data as source for the solar radiation impacts the PV potential estimate. System efficiency is assumed equally throughout most studies. S1, which was published over a decade ago, assume a lower value of 10%. S5 quote a value of 10.3% which is derived from measurements. However, a higher value of 17% average module efficiency and 80% performance factor appear realistic when considering the constantly improving performance of PV installations. These values used in S2-S4 are confirmed by the results obtained from the detailed model of module and inverter efficiencies used in S6.

The final technical PV rooftop potential ranges from the lowest estimate of 15TWh by S1 up to 53TWh by S4. The lower values are based on a smaller ground floor area and hence likely underestimate the total available roof area for PV installation. The upper estimates are characterized in particular through a high ratio of available area to ground floor area and high tilted radiation. The former leads to an overestimation of technical PV potential, as superstructures and roof geometry have a significant impact on the total available roof area. The latter is largely based on the meteorological input data. Estimates based on MeteoSwiss data, which is corrected for high altitudes [6], have the highest G_t . As the satellite sources are known to over-estimate solar radiation by 2-3% [5], the upper estimates of G_t should be considered slightly optimistic.

Table 2. Quantitative comparison of results from six studies of rooftop PV potential in Switzerland.

Study	A_{floor} (km ²)	C_R (%)	A_{PV} (km ²)	G_t (kWh/m ²)	<i>Suitable roofs</i> (%)	η_{sys} (%)	E_{PV} (TWh)	\hat{E}_{PV} (kWh/m ²)
S1	349.0 ^a	72	251.3 ^a	1,088*	55	10	15.04	108.8
S2	407	81	328	662*	60.5 ^b	13.6	17.86	90.6
S3	269	94	252	786*	60.5 ^b	13.6	16.29	107.6
S4	581.5 ^c	74.8 ^c	314.1 ^c	1,243 ^c	72.2 ^c	13.6	53.09 ^c	169.0
S5	485	100	485	1,176 ^d	70.1 ^d	10.3	41.32*	121.5
S6	581.5 ^c	45.9	267	1,186	56.4	13.8	24.58	163.2

* Derived from equation (3); ^{a,b,c,d} See approximations in Section 4; bold values quoted directly from study

5. Conclusions

Throughout the past two decades, six studies have estimated the technical rooftop solar PV potential in Switzerland. During this time, the methodologies have changed significantly, moving from simple rules of thumb to data-driven approaches that process very large datasets. Different datasets and methods lead to widely varying potential estimations, ranging from 15TWh to 53TWh. A quantitative comparison showed that in particular the estimation of available roof area for PV panel installation, the source of the solar radiation data as well as the method to compute shading effects on rooftops has a large impact on the results. The analysis also showed that methods based on Machine Learning have achieved good results with using only a small amount of data, indicating that ML is an effective tool to handle missing data and to estimate uncertainty. Uncertainties can be systematically reduced by using powerful processing methods, as larger and more accurate data become available. This is particularly important for a reliable extraction of the available roof area for PV installation, which is currently the most uncertain aspect of the rooftop PV potential estimation. A promising approach is the use of Machine Learning to extract these areas from high-resolution satellite images, for example using deep learning.

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