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Assessment of rooftop photovoltaic potentials at the urban level using publicly available geodata and image recognition techniques

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ABSTRACT

The local generation of renewable electricity through roof-mounted photovoltaic (PV) systems on buildings in urban areas provides huge potentials for the mitigation of greenhouse gas emissions. This contribution presents a new method to provide local decision makers with tools to assess the remaining PV potential within their respective communities. It allows highly detailed analyses without having to rely on 3D city models, which are often not available. This is achieved by a combination of publicly available geographical building data and aerial images that are analyzed using image recognition and machine learning approaches. The method also employs sophisticated algorithms for irradiance simulation and power generation that exhibit a higher accuracy than most existing PV potential studies. The method is demonstrated with an application to the city of Freiburg, for which a technical PV electricity generation potential of about 524 GWh/a is identified. A validation with a 3D city model shows that the correct roof azimuth can be determined with an accuracy of about 70% and existing solar installations can be detected with an accuracy of about 90%. This demonstrates that the method can be employed for spatially and temporally detailed PV potential assessments in arbitrary urban areas when only public geographical building data is available instead of exact 3D city model data. Future work will focus on methodological improvements as well as on the integration of the method within an urban energy system modeling framework.

1. Introduction

There is a worldwide consensus that greenhouse gas emissions should be substantially reduced over the next few decades in order to mitigate climate change (IPCC, 2015). This can only be accomplished through a massive decarbonization of the energy system. One of the most important levers in this endeavor are combinations of energy efficiency measures and renewable energy resources in cities, which will have to play a crucial role in the energy transition (IEA, 2016).

In order to develop local schemes and make informed decisions for the transition to renewable energies, policy makers need to be provided with accurate information on the potential contribution from each of these measures on global as well as on regional and local levels.

The local generation of clean power through PV systems on building roofs, in particular, provides huge potentials that are usually economically viable. Compared to other available options, PV has higher public acceptance, partly because there is less competition for land or other resources.

The assessment of the (remaining) potential for power generation from PV is an important field of study. Methods and tools that enable local decision makers to assess PV potentials in their respective communities are of vital importance for the energy transition. The literature review in Section 2 shows, however, that currently there are no tools available that allow local decision makers to assess these potentials in high detail and accuracy without first having to acquire large amounts of data. With this contribution, the authors intend to address this issue.

Since the requirements for detailed PV potential analyses usually include data that is not publicly available and, especially in smaller municipalities, can not be easily obtained, the objective of this contribution is to present a method for detailed urban PV potential assessment that relies solely on publicly available data and can be applied universally. The authors improve upon existing work as well as their previous publications (e.g. Mainzer et al., 2016) in a number of points:

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1. high-detailed, bottom-up PV potential analysis in the absence of 3D model data,
2. discrete number of actually installable modules instead of just the area,
3. consideration of roof objects, e.g. chimneys and windows,
4. exact irradiance simulation with high temporal resolution (1/4 hourly),
5. detailed, non-linear power generation model with consideration of temperature, module and inverter characteristics,
6. consideration of already installed PV modules.

The present literature on the subject is analyzed in Section 2. In Section 3, all steps of the method that was developed are described in detail. Section 4 presents results from an example application of the method to the city of Freiburg, Germany. These results are further analyzed, validated and discussed. In Section 5, the findings are concluded.

2. Literature review

Several publications have already addressed the problem of identifying PV potentials. The main steps in PV potential estimation methods include the assessment of the available area for PV modules, the simulation of solar irradiance on the tilted module surfaces and the calculation of produced electrical power from the irradiance on these modules. Martín-Chivelet (2016) provides an overview of different methodologies that are employed for each of these steps. As discussed in the following section, various levels of detail can be achieved with different approaches. In addition, Freitas et al. (2015) also provide an overview over solar potential in the urban environment with a focus on solar radiation models.

For large-scale analyses, methods based on statistical data, e.g. building databases, are commonly used. Schallenberg-Rodríguez (2013) provides a review of methods for the assessment of the available roof area using statistical building data and roof utilization factors, the calculation of monthly solar radiation values on inclined surfaces and yearly electricity production. The scale of assessments using these methods is rather large, e.g. Schallenberg-Rodríguez (2013) applies them to the Canary Islands and Defaix et al. (2012) assess the PV potential in the EU-27. Due to data availability, however, the detail of these approaches is limited, which results in a low spatial and temporal resolution of the assessed potentials. Other approaches combine statistical methods with geographical information systems (GIS) to increase the spatial resolution, e.g. Mainzer et al. (2014) assess the PV potentials for Germany on a municipal level.

If more detail and higher spatial resolutions are required, bottom-up methods that rely on 3D model data are common. For instance, Romero Rodríguez et al. (2017) use a 3D city model to calculate the total roof area and received solar irradiance for the German County district Ludwigsburg. Combined with factors for the share of usable roof area and technical efficiency as well as economic constraints, they are able to calculate the technical and economic PV potential at an urban scale in high resolution.

Although 3D models are becoming increasingly common, in most cases they are not freely available or, especially for smaller municipalities, not available at all. Additionally, the heterogeneity of data formats is a hindrance to using them for arbitrary regions within the same model framework. The methods used to create 3D city models differ, but usually either Light Detection and Ranging (LiDAR, e.g. Srećković et al., 2016; Brito et al., 2012; Nguyen and Pearce, 2012; Jakubiec and Reinhart, 2013) or stereophotogrammetry (e.g. Theodoridou et al., 2012; Jo and Otanicar, 2011; Wittmann et al., 1997) are used. Both methods can provide very detailed 3D models, but both also require significant investments in terms of money and time. Surveying flights in order to obtain the data and manual labor in order to create the 3D model are required. Similar methods that rely on 3D models are employed in commercial applications,[1] which can be used to estimate the PV yield for single buildings. These approaches are in some cases very detailed, however, they do not allow the assessment for larger regions and they are usually available only in certain regions.

Although some of the above mentioned methods are very detailed, they still use many simplifications that could easily be improved upon. For example, most studies apply fixed utilization factors to consider the fact that in most cases, the available roof area can only partially be used for PV installations due to obstructions like chimneys or windows. They also calculate the number of modules that can be installed on the roof area with a simple packing factor, instead of calculating how many PV modules could actually fit inside the respective roof shape. Examples for these simplifications can be found in Martín-Chivelet (2016), Schallenberg-Rodríguez (2013), Defaix et al. (2012), Singh and Banerjee (2015), Mainzer et al. (2014), Fath et al. (2015), Mavromatidis et al. (2015) and others. Most published methods also apply very simple models to calculate the produced electricity from the received irradiance, usually by applying a fixed module efficiency and performance ratio of the system, instead of considering the non-linear effects of temperature, module type, inverter utilization etc. This is a well-known field of study, though, and more sophisticated algorithms are available and can easily be implemented, see e.g. Drews et al. (2007) for module temperature modeling, Huld et al. (2010) for module efficiency calculation and Macêdo and Zilles (2007) for inverter efficiencies.

With the higher detail that improvements in these areas could provide, the results could be better employed in studies that examine the integration of PV in the energy system. For example, Killinger et al. (2015) determine the optimal investment in differently oriented PV systems in the context of four German regions with regard to their ability to match the local demand, reduce strain on the power grid or replace fossil power production. On a larger scale, Mainzer et al. (2014) analyze how much of the available PV potential in each German municipality could be exploited before electricity would have to be fed back into the national grid. The integration of PV into the distribution network infrastructure is analyzed by Srećković et al. (2016) in a case study for Maribor, Slovenia and by Wegertseder et al. (2016) for Concepción, Chile.

Currently, there are no methods available that can provide PV potential assessments with a high spatial resolution when 3D model data is not available. However, a number of approaches that deal with the problem of acquiring geographical data that is not (publicly) available have been published in the past. Taubenböck (2007) presents a method to estimate the height of buildings based on an analysis of shadow lengths in satellite images. Assouline et al. (2017) use machine learning (support vector machines) to spatially extrapolate weather variables, and to estimate roof characteristics based on training data from 42 communes in Switzerland. Miyazaki et al. (2016) use neural networks to automatically derive building locations from Bing Map aerial images.

Bergamasco and Asinari (2011) present a methodology that estimates the suitability of a roof based on pixel colors and brightnesses. Hazelhoff and de With (2011) attempt to automatically detect buildings with a gable roof in rural areas. Both of these approaches could be used in the context of PV potential estimation, however, both also rely on very-high-resolution aerial images, which have been provided by local authorities in connection with a specific project.

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[1] One example is a cooperation of E.ON and Google, available at www.eon-solar.de.