



Influence of vegetation canopies on solar potential in urban environments



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ABSTRACT

Solar energy is clearly a promising option among the many available sources of renewable energy, and its market has seen outstanding growth. Careful evaluation to determine suitable locations for photovoltaic installations is needed, however, as their efficiency is highly dependent on exposure to sun. Especially in urban environments, quantifying the shadows cast by other buildings and vegetation canopies may be essential. In the present study, we used light detection and ranging (LiDAR) data and geographic information systems (GIS) to assess the influence of shading vegetation on solar irradiation estimates in five European towns. The fraction of annual solar irradiation lost to shading by existing vegetation ranged between 3% and 11%. The fraction lost was higher in winter and lower in summer. Due to greater incoming solar radiation in summer, however, more than 50% of annual loss was accounted for in summer. We suggest that at the broad scale of whole cities the influence of vegetation on rooftop solar potential estimates is negligible (especially in densely populated areas). Analyses which do not consider vegetation because of data availability nevertheless provide valuable insight into localities' solar potential.

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1. Introduction

Use of energy from renewable sources is an important objective of the European Union's energy policy (see Calvert, Pearce, & Mabee, 2013 for review of progress in renewable energy mapping). According to EU Directive 2009/28/EC, the adoption of which established a common framework for production and promotion of energy from renewable sources, the EU should achieve a 20% share from renewable energy sources in total electricity consumption by 2020. Among many available sources of renewable energy, solar energy is clearly a promising option and its market has seen outstanding growth in recent years (Devabhaktuni et al., 2013). In some countries, however, incentives for employing photovoltaic (PV) installations has led to a situation wherein they consist predominantly of large ground-mounted facilities located on agricultural land, also referred to as solar farms (Gallay, Kaňuk, & Hofierka, 2014). Solar farms are often a preferred solution among investors due to their high economic returns, but their negative impacts are typically not considered. Solar farms jeopardize wide agricultural

terrains and compete for limited land with other renewable energy sources, such as bioenergy feedstock systems (Calvert & Mabee, 2015). An adequate alternative to solar farms may be PV installations on rooftops in urban environments (e.g., Santos et al., 2014), and these, too, have been promoted by recent changes in support schemes for PV installations in some countries (Hofierka, Kaňuk, & Gallay, 2014). Moreover, solar potential has been proposed as important design parameter in urban planning (e.g., Kanters & Horvat, 2012).

The estimation of rooftop solar potential in urban environments has been of considerable interest in recent years. At a very broad scale, the solar potential of building-integrated photovoltaics in EU member states is estimated to be more than 22% of expected European 2030 annual electricity demand (Defaix, Van Sark, Worrell, & De Visser, 2012). Urban environments present challenges, however, due to the complex urban morphology. As more homeowners and businesses investigate the feasibility of rooftop PV installations, there is growing demand for data and tools enabling more accurate prediction of incident solar radiation.

Such tools have long been implemented in the most frequently used GIS software: r.sun (Hofierka & Šúri, 2002) in GRASS and Solar Analyst (Fu & Rich, 1999) in ArcGIS. However, only with increasing

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availability of spatial data of adequate quality and extent, such as light detection and ranging (LiDAR) data, have these tools inevitably become common in the successful development of photovoltaic systems in urban environments. For example, solar potential has been estimated for the city of Bardejov in Slovakia (Hofierka & Kaňuk, 2009), a small parish in the city of Lisbon (Santos et al., 2014), and downtown San Francisco (Li, Zhang, & Davey, 2015). Moreover, many cities across the world have developed their own solar maps to support the decision-making process and identify locations suitable for PV installations. These typically consist of a user-friendly web-based interface that visually provides information about solar irradiation and instructs users about the costs and benefits of PV installations. To examine a list of existing solar maps, see Kanters, Wall, and Kjellsson (2014) and Freitas, Catita, Redweik, and Brito (2015). Given the complexity of factors influencing incident solar radiation, the most important factor in urban environments relates to shadowing effects. For example, Sarralde, Quinn, Wiesmann, and Steemers (2015) have explored the relationship between urban morphology and the potential to harvest solar energy and found as much as a 9% increase in rooftop solar potential when the urban form is optimized.

In seeking suitable locations for photovoltaic installations, it is essential to quantify the shadows cast by other buildings and vegetation canopies. Vegetation is an important component of the urban environment, and it has a multiplicity of functions: reducing air and noise pollution, mitigating the urban heat island effect, and beautifying the urban environment (Smardon, 1988). However, it is also a source of shadow which may limit incident solar radiation. Moreover, it is often considered only simplistically or even excluded from solar radiation modelling (Freitas et al., 2015). That is due mainly to a lack of appropriate data in developing countries (e.g. Araya-Muñoz, Carvajal, Sáez-Carreño, Bensaid, & Soto-Márquez, 2014). Only two studies to date have directly addressed the influence of vegetation shading on rooftop solar potential.

It is difficult to draw conclusions from these studies, because their results differ significantly. Levinson, Akbari, Pomerantz, and Gupta (2009) found annual solar irradiation loss due to vegetation of as much as 8%, and Tooke, Coops, Voogt, and Meitner (2011) reported even 38%. Moreover, Tooke et al. (2011) limited their study to typical days (solstices and equinoxes) for reasons of computational efficiency and Levinson et al. (2009) derived shapes of tree canopies manually from orthophotos, which is a laborious and time-consuming process for larger areas. In the present study, we assess the importance of including vegetation data into models and evaluate its impact on monthly rooftop solar irradiation estimates while utilizing all the advantages of LiDAR data. Whereas previous studies have concentrated their efforts on parts of larger cities, mostly because of data availability, we rather selected four small European towns to encompass different urban morphologies.

2. Methodology

2.1. Study area

The study encompassed five small European towns (Fig. 1) located in the Czech Republic (Pec pod Sněžkou), Denmark (Kalvehave), Finland (Pellesmäki), Slovenia (Lukavci), and the Netherlands (Macharen). The locations differ in latitude, topography, and morphology. Those in the Czech Republic, Finland are representative of cities with sparse buildings, whereas those in the Netherlands, Denmark and Slovenia are representative of more developed cities with dense housing (Table 1). All study areas were cropped to be within a rectangle of 1 km², which represents majority of towns' built-up areas and only distant buildings were removed from the analyses. Appendix A in the Supplementary

Material shows maps of the study areas (Fig. A.1–A.5). The workflow depicted in Fig. 2 was used to evaluate rooftop solar potential and estimate the influence upon it of shadowing vegetation.

2.2. LiDAR data

LiDAR is an active remote sensing device that consists of three components: a laser scanner, which emits and receives laser pulses; an inertial measurement unit (IMU), which detects changes in pitch, roll, and yaw; and the Global Positioning System (GPS). By recording the exact location of the sensor and the time it takes for each laser pulse to return, a detailed three-dimensional dataset stored as a point cloud is produced over a given area (Wehr & Lohr, 1999). LiDAR provides a highly accurate, fast, and easy way to collect data, and many state governments have collected high-resolution aerial LiDAR data for various purposes. Some of them have made this data freely available so that everyone can benefit from their advantages. In this study, we used airborne LiDAR datasets which are freely available (Table 2).

2.3. LiDAR-derived footprint and DSM

A building's footprint and digital surface model (DSM) are required for modelling rooftop solar irradiation. While many previous studies have had to compile heterogeneous sources of spatial data, which may have led to serious drawbacks with respect to data accuracy (Agugiaro, Nex, & Remondino, 2012), we grasped the comprehensiveness of LiDAR and used it as a single reliable source. See study by Martin, Dominguez, and Amador (2015) for a review of existing studies that applied LiDAR data to assess solar potential in urban environments.

We used LAStools to detect buildings and vegetation from LiDAR data (LAStools, 2014). First, point clouds were classified into ground and non-ground returns (*lasground*) and the height of each return above the ground was computed (*lasheight*). Second, discrimination was made between returns representing buildings versus vegetation (*lasclassify*). It is still challenging to accurately separate buildings from vegetation, however, and particularly when branches of trees are close to buildings' roofs. Thus, all point clouds were manually post-processed (edited) and errors corrected.

To model potential solar irradiation, building footprints should represent most accurately the outlines of the building roofs. There exist several approaches for acquiring building footprints. These can be acquired from cadastre data (Esclapés, Ferreira, Piera, & Teller, 2014), manually digitized from high resolution orthophotos (Hofierka & Kaňuk, 2009; Levinson et al., 2009), or derived directly from LiDAR (Tooke et al., 2011). Manual digitization is a laborious process and cadastre data often suffer from inaccuracies (Agugiaro et al., 2012). Direct generation of building footprints from classified LiDAR data, as done in this study, is a straightforward method. Boundary polygons that enclose all points representing a particular roof were created using LAStools (*lasboundary*) and then simplified by 'Simplify Polygon' and then 'Simplify Building' tool in ArcGIS 10.2 (ESRI, 2014).

DSMs are 2.5D representations of the Earth's surface including all objects on the ground (e.g., buildings, vegetation). The term 2.5D refers to a model that is embedded in three dimensions (3D), but is not able to represent all 3D shapes, such as caves and overhangs. This is a major drawback when calculating incident solar radiation. In order to determine the effect of vegetation canopies on the amount of incident radiation, we created two DSMs: (1) *vegetation included*, and (2) *vegetation excluded*. Both DSMs were derived from LiDAR at a spatial resolution of 0.5 m. The first raster, which represents the actual situation with vegetation, was created using the complete LiDAR point cloud. The second represents a hypothetical

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