1	Photovoltaic generation on vertical façades in urban context from open
2	satellite-derived solar resource data
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13 14	Abstract
15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34	Solar radiation incident at building façades and elements in an urban context is essential in determining the energy production on building rooftops and vertical façades. The proper determination of solar irradiance incident on a vertical façade needs quality input of the components of solar radiation and a high resolution digital surface model with the heights of buildings and other elements in the urban area of study. In this work a thorough methodology for modeling PV generation, in hourly basis, at building façades with open available data and methods is presented. Hourly data of satellite-derived solar irradiance is used with high resolution digital model from LIDAR information to estimate with the Sandia model the PV generation of five small arrays at west, south and east façades of a building in Madrid. PV output modeled for west and south arrays are in rather good agreement with the monitored experimental data of the production. RMSE of 8% and 12% was observed for the monthly power predicted for west and south facades, respectively. The east façade case was much more challenging due to variability of shadows it receives from the nearby large deciduous trees throughout the year, which results in high uncertainty in the shading influence estimation of PV production in building façades from open available information regarding both solar resource, open modeling tools and urban topography, even in a very challenging conditions associated to the variability of trees canopy.
35 36 37	Keywords: BIPV; PV modeling; Solar Radiation databases; Sky View Factor; Digital Surface Model; partial shading of PV arrays
38 39	1. Introduction
40 41 42 43 44 45	Solar photovoltaics (PV) and solar thermal systems deployments in urban environments are gaining interest as drivers of decentralization of electricity and heat production. Both are key elements in the concept of Nearly Zero-Energy Buildings (nZEB) aimed at achieving buildings almost independent from the external electrical grid through proper designed features and the use of renewable energy sources (Marszal et al., 2011). In the case of PV, the International Energy Agency, through the Task 15 of the programme IEA-PVPS (PVPS, 2021), is gathering

efforts in promoting and accelerating the penetration of both BIPV (Building Integrated
PhotoVoltaics) and BAPV (Building Applied PhotoVoltaics), and delivering updated reports on
important aspects as regulation, definition and characterization, user needs and research.
Solar potential studies in urban landscape can include ground, roofs and vertical façades of
buildings.

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52 Many studies in the literature dealt with solar potential estimation on rooftops using 53 geographic information systems (GIS) to incorporate the influence of urban obstructions to the 54 incoming solar radiation (Bódis et al., 2019; Brito et al., 2012; Jakubiec and Reinhart, 2013; 55 Khan and Arsalan, 2016; Singh and Banerjee, 2015; Verso et al., 2015). However, in the past 56 recent years additional studies include methodologies for estimating solar potential also in 57 vertical façades (Catita et al., 2014; Desthieux et al., 2018; Hofierka and Zlocha, 2012; Lindberg 58 et al., 2015; Lou et al., 2016; Redweik et al., 2013). A thorough review on modeling the solar 59 potential in urban context can be found in the recent literature (Freitas et al., 2015). Recent 60 studies combine GIS, physics models and machine learning algorithms at national scale 61 (Assouline et al., 2018; Walch et al., 2020). Moreover, recent contributions are conducting also 62 to the availability of open and powerful tools broadening the possibilities of new studies and 63 analysis. For instance this is the case of SEBE (Solar Energy on Building Envelopes) model which 64 is incorporated in UMEP (Urban Multi-scale Environmental Predictor), a plugin for QGIS 65 software (QGIS, 2021). SEBE model estimates solar irradiance on ground surfaces, building 66 roofs and walls from digital surface model (DSM) and solar position (Lindberg et al., 2015; Ratti 67 and Richens, 1999).

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69 The models and tools for estimating solar potential in complex urban environment require also 70 detailed information of solar resource. Solar radiation data on vertical surfaces are not 71 generally available from measurements and the procedure involves having data of the three 72 components of solar irradiance for horizontal surface: Global Horizontal Irradiance (GHI), 73 Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DIF). Then, the subsequent 74 use of transposition models is needed afterwards to derive the incident solar irradiance at 75 vertical surfaces. The accuracy and quality of the initial solar radiation data plays a significant 76 role on the final uncertainty since there are many intermediate steps in the procedure of 77 estimating solar irradiance incident on façades. Satellite-derived solar irradiance data is 78 probably the best choice nowadays since there are several high quality products that are freely 79 available(Polo and Perez, 2019; Sengupta et al., 2017). Time series of GHI, DNI and DIF can be 80 obtained on an hourly basis from several databases with rather good quality (de Freitas 81 Moscardini Júnior and Rüther, 2020; Huld et al., 2012; Polo et al., 2020; Psiloglou et al., 2020; 82 Riihelä et al., 2015; Urraca et al., 2017; Yang, 2018; Yang and Bright, 2020). Afterwards, 83 transposition models are then needed to estimating solar irradiance at an inclined and 84 arbitrarily oriented surface using the three components (GHI, DNI, DIF) as input. There is a very 85 large list of transposition models elsewhere and recent studies contain useful information on 86 their accuracy and associated difficulties and problems (Gueymard and Ruiz-Arias, 2016; Yang, 87 2016).

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89 This work presents a thorough methodology for modeling in detail the PV generation of five 90 small PV arrays placed at the vertical façades of a building in Madrid using as input open 91 satellite-derived solar radiation data and LIDAR information. A DSM is built from the LIDAR 92 data to estimate shading and the corresponding sky view factor (SVF). Two years of hourly 93 solar radiation is used as input to derive solar irradiance in high detail for the facades of the 94 building. Most works in the literature employ GIS for studying the potential mainly on rooftops 95 and less frequently in facades in terms of yearly values or annual yield, but very few studies 96 presents estimations at hourly basis and assessment with real monitored PV arrays working on 97 facades of a building. The results show the benefit of the methodology for modeling the PV

generation of modules at façades and also evidence the potential problems associated to the
presence of large trees near the façade that may affect to the proper shading effect
determination; particularly interesting is the case of deciduous trees, which opacity changes
throughout the year.

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2. Description of the case study and experimental data

105 The building under study is the so-called *Building 42* of Ciemat headquarters area, 106 placed in the university campus in Madrid (40.4551° North, -3.73° East). This building 107 houses five individual small PV arrays (each one connected to a different single 108 inverter) distributed in the upper part of the east, south and west facades. The 109 orientation of the building is slightly deviated to the west (about 9°) and thus the 110 façades azimuth are 351°, 81°, 171° and 262° for façades north, east, south and west, 111 respectively. Figure 1 shows the domain area used in this work and pictures of the PV 112 arrays in facades east, south and west. The east facade contains three identical PV arrays of 7sx2p modules (named East S, East C and East N arrays, respectively), the 113 114 south façade has one array of 7sx4p modules, and the west façade includes one 8sx2p 115 PV array. Table 1 summarizes the module and inverter characteristics of all the arrays. Additional details on the building structures, PV systems and monitoring can be found 116 in a previous descriptive work (Martín-Chivelet et al., 2018). 117

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Figure 1. a) Area of study of Ciemat headquarters. b) East façade with three PV arrays
highlighted. c) South façade with the corresponding PV array. d) West façade with the
PV array used in this work.

128 Table 1. Main characteristics of the PV arrays

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Array	Configuration	Module	Power (W)	Inverter	Power (kW)
East_N	7sx2p	SunPower E20-327	327	Fronius IG Plus 50 V-1	4
East_C	7sx2p	SunPower E20-327	327	Fronius IG Plus 50 V-1	4
East_S	7sx2p	SunPower E20-327	327	Fronius IG Plus 50 V-1	4
South	7sx4p	SunPower E18-325	305	Fronius IG Plus 100 V-3	8
West	8sx2p	SunPower E20-327	327	Fronius IG Plus 50 V-1	4

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131 Different electrical parameters of each array as well as some local meteorological 132 variables are being monitored. In particular, voltage, current and power of each 133 inverter are available. In addition, module temperature of one single module from each array is measured using T type thermocouples. Global horizontal irradiance (GHI) 134 135 is measured in the rooftop of the building with a thermopile pyranometer and vertical 136 irradiance in east, south and west orientations of the building are also recorded by several calibrated cells placed at the top of a mast in the building rooftop (Figure 2). 137 138 Unfortunately there were not available long and quality measurements of direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI). Figure 2 shows also 139 140 how the modules were integrated and fastened to the façade in the upgrading work of 141 the building. PV modules are integrated into the upper areas of a new ventilated 142 façade, built as part of the rehabilitation project for Ciemat building 42, which was 143 aimed at improving the building's structural condition and energy efficiency. PV 144 modules occupy a total surface area of about 176 m2.

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Figure 2. a) Mast placed at the building rooftop with calibrated cells for measuring vertical irradiance at east, south and west orientations. b) Solar panels integration with the façade.

3. Solar resource data

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The basic solar resource data used as input in this work consisted of two years (2017 155 and 2018) of hourly data of the three solar irradiance components (GHI, DNI and DIF) 156 delivered by CAMS (Copernicus Atmosphere Monitoring Service) Radiation Service 157 with a spatial resolution of 3 km at nadir (Schroedter-Homscheidt et al., 2019). CAMS 158 159 Radiation Service (Copernicus, 2021) is a high quality database of solar irradiance

160 based on Heliosat-4 methodology (Qu et al., 2017). The method combined the cloud 161 properties derived from Meteosat Second Generation (MSG) satellites with fast radiative transfer model McClear (Lefèvre et al., 2013). CAMS GHI hourly data 162 compared with the GHI measurements on the building rooftop resulted in mean bias 163 164 deviation (MBD) of -0.5 % and root mean square deviation (RMSD) of 17.4 %. Figure 3 shows a scatter plot for the assessment of GHI delivered by CAMS Radiation Service for 165 the period 2017-2018; the corresponding R² for this scatter plot is 0.95. Despite there 166 is no quality measurements of DNI for evaluating the uncertainty of DNI derived by 167 168 CAMS Radiation Service it is expected to be higher than the uncertainty for GHI. For instance, evaluation of CAMS radiation service in several ground stations in Morocco 169 170 resulted in RMSD for hourly DNI in the range of 26-39% (Marchand et al., 2018). 171 Nevertheless, it should be remarked that CAMS Radiation Service is one of the best and more accurate free and open products for solar radiation data derived from 172 173 satellite imagery (Yang and Bright, 2020).





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Figure 3. Scatter plot of hourly GHI estimated by CAMS vs. experimentalmeasurements in Building 42.

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- 4. Solar irradiance at vertical façades
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- 4.1 Sky view factor and Shadow calculation
- The sky view factor (SVF) is a simple parameter describing the part of the sky that is not obscured by the surroundings for a given point (Lindberg and Grimmond, 2010). It can be defined as the ratio of the sky hemisphere visible from the ground (Bernard,

- 188 2018). The SVF and the shadowing in the facades of a building can be computed from a high-resolution digital surface model (DSM) derived from LIDAR data. LIDAR data offers 189 the height of a ground area with very high resolution (including buildings, trees, 190 structures, etc). In Spain LIDAR data is supplied by the Spanish Geographic Institute 191 (IGN) through a download service (Centro Nacional de Información Geográfica, 2021). 192 193 194 In this work a DSM of the area under study is obtained with the use of LASTools (a 195 powerful library for reading and extracting information from compressed LIDAR files) and QGIS. The resulting raster DSM of the area of Ciemat including the Building 42 and 196 surrounding buildings, elements and trees is shown in figure 4. The DSM shown in this 197 198 figure covers the same area of that shown in Figure 1 a), so that the identification of 199 the building under study in figures 4 a) and b) is straightforward. It should be remarked 200 that north and east façades of the building have many large trees placed close to the 201 building, while south and west-south facades have mainly other buildings in the
- 202 surroundings.



Building 42

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205	Figure 4. a) Geotiff raster	of DSM. b)	3-D view of DSM.
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207 Four artificial façades for the target building have been created by selecting the 208 corresponding x-utm and y-utm coordinates of the points delimiting each building 209 façade in the DSM with a resolution of around 25 cm in length and 0.5 m in height. The 210 total height of each artificial façade is 15 m, so that it is higher than the actual façades 211 heights of 8 and 10 m, depending on the façade. Thus a façade is a matrix of 31 rows 212 (denoting points at different heights) by 150-175 columns (defined by x-utm and y-utm coordinates of the real façades). 213

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215 For each point (i, j) in the façade matrix, the SVF for the façade F is computed by the 216 following expression (Böhner and Antonić, 2009):

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$$SVF^{F}(i,j) = \frac{1}{N} \sum_{n=1}^{N} [\cos\beta \cos^{2}\phi_{n}(i,j) + \sin\beta \cos(n-\alpha_{F})(90 - \phi_{n}(i,j) - \sin\phi_{n}(i,j)\cos\phi_{n}(i,j))].$$
(1)

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222 Where N is 360°, β is the tilt angle of the surface (90° for a vertical façade), n is a 223 direction in azimuth (it ranges from 1 to 360 in steps of 1°), α_F is the azimuth of the 224 façade F, and $\phi_n(i,j)$ is the horizon angle of point (i,j) in the azimuth direction 225 determined by n. The horizon angle $\phi_n(i,j)$ is determined by the angle of elevation of 226 the highest obstacle (point in the DSM) that the point (i,j) views in the azimuth 227 determined by n.

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Figure 5 shows the SVF computed for the four façades of *Building 42* taking into account the obstacles in the area delimited by the DSM. It can be clearly appreciated the strong influence of the large trees on the North-East corner of the building.

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Figure 5. SVF computed for the four façades of CIEMAT Building 42.

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Shadows are computed in hourly basis for each element of the façade (25 cm wide and
50 cm in height) as a parameter, that can only takes two values, *Sh*=1 if the element is
illuminated and *Sh*=0 if the element is shadowed. Thus, for every façade we have a
matrix of shadow for every hour indicating which elements in the façade are

242 completely shadowed and which ones are completely illuminated every hour.

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4.2 Solar irradiance at vertical façades

In order to estimate the incident hourly solar irradiance at each point of the façade *F*we have assumed the following approach,

$$G^{F}(i,j) = DNI\cos(AOI)Sh(i,j) + Diff^{F}(i,j) + \frac{1}{2}\rho^{F}GHI , \qquad (2)$$

where AOI is the angle of incidence which depends on the solar elevation and 255 256 azimuth angles and on the surface's tilt (90° for every façade) and azimuth angles, $Diff^{F}(i, j)$ is the sky diffuse irradiance for the element (i, j) of façade F, and ρ^{F} is the 257 258 effective albedo for façade F, defined here as the average albedo of the ground and 259 surrounding surfaces that can reflect solar irradiance towards the façade (the values of 260 0.2 has been chosen for the effective albedo). Therefore, the incident solar irradiance 261 on the façade element is the sum of three contributions, the direct irradiance 262 projected to the surface taking into account the shading, the sky diffuse irradiance and 263 the reflected irradiance due to ground and other surfaces and elements in the 264 surrounding. The Diffuse irradiance is computed from the three components of 265 horizontal irradiance by the Perez model with modifications to take into account the 266 sky view factor of each element in the façade (Perez et al., 1990, 1987). The sky diffuse irradiance is then estimated by, 267

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$$Diff^{F}(i,j) = Cir^{F}Sh(i,j) + DIF SVF^{F}(i,j) + Hor^{F},$$
(3)

being Cir^{F} and Hor^{F} are the circumsolar diffuse component and horizon brightening 271 diffuse component of the solar radiation estimated by Perez model, respectively. 272 273 Therefore, the main modification to the original Perez model for tilt surface consisted 274 on taking into account the shading in the circumsolar diffuse component and the sky 275 view factor of every façade element in the isotropic diffuse irradiance instead of the 276 sky view factor determined only by the tilt angle (0.5 for the case of a vertical surface). 277 Therefore, using the GHI, DNI and DIF satellite-derived components provided by CAMS 278 Radiation Service as input and the sky view factor and shading estimated from the 279 DSM is suitable to estimate the incident solar irradiance at each façade element. 280

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4.3 Evaluation of solar radiation estimations at façades

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283 In order to evaluate the uncertainty of the solar irradiance estimations made on the 284 building façades we have compared them with the measurements of the calibrated solar cells placed at the top of a mast on the building rooftop (Figure 2). The 285 286 corresponding MBE, RMSD and MAD (Mean Absolute Deviation) are shown in table 2. 287 Figure 6 shows the east, south and west solar irradiance estimated compared with 288 measurements in hourly basis for a few days and the corresponding scatter plots. The 289 R^2 estimated for these scatter plots were 0.73, 0.89 and 0.90 for the east, south and 290 west facades, respectively.

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295 Table 2. Error metrics for solar irradiance estimated at vertical façades

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Façade	MBD (%)	RMSD (%)	MAD (%)
East	5.7	57.3	32.0
South	5.6	29.8	18.4
West	-6.2	32.1	18.8

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As shown in both the table and the scatter plots of figure 6 much higher uncertainty resulted in the estimations of solar irradiance at the east façade. As a consequence much higher uncertainties are also expected in modeling those PV arrays placed on east façade.

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303 The scatter plot for east façade shows a set of data that are particularly

304 underestimated (Figure 6). This underestimation is due to the uncertainty associated

to the large deciduous trees in front of the east façade of the building. On the one

306 hand, DSM information that comes from LIDAR data might not include recent possible

307 changes in the natural vegetal cover (i.e. tree pruning), or refurbishment works after

308 LIDAR flights; on the other, during fall and winter seasons the deciduous trees opacity

309 is much less than in spring and summer, and consequently direct radiation can reach

the wall of the building while the modeling calculates a shadowing. Therefore, the line

of deciduous trees close to the east facade, taller than the building height, is very

challenging for modeling both the solar irradiance and the PV generation at the façade.

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5. Modeling the PV generation at the three façades

The energy generation of the five PV arrays listed in table 1 has been modeled for two years (2017 and 2018) with the Sandia Array Performance Model (SAPM) using as input the solar irradiance, in hourly basis, estimated at the façade points, with a

resolution of 50x25 cm, and the module temperature measured at each array. Back
panel temperature was measured with one thermocouple for every array at the rear
side of the modules, and was directly input to the SAPM model. SAPM is available
under the PV Performance Modeling Collaborative initiative (King et al., 2007, 2004).
SAPM model is included in the PV lib library that can be freely downloaded from the
PVPCM site (PVPCM, 2021) and has shown to be very flexible and accurate (Gurupira
and Rix, 2017; Polo et al., 2016; Stein and Farnung, 2017).

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334 Since the irradiance incident at each array varies along the surface due to shading, the DC part of the PV generation has been modeled individually for every single module in 335 336 the array and then the array configuration has been taken into account for estimating 337 the DC generation of the whole array. Thus, SAPM model is used to model the DC 338 power of every single module in the array using as input the average incoming solar 339 irradiance over the module area and the module temperature measured (we have only 340 one measuring point for the module temperature for each array). Modeling partial 341 shading in PV arrays is complex and can involve to deal module by module, or cell by cell, with the whole I-V curve (Alonso-García et al., 2006; Algaisi and Mahmoud, 2019; 342 343 Galeano et al., 2018; Seyedmahmoudian et al., 2013). Shading losses depend on the 344 series-parallel configuration of the array, the number and distribution of by-pass and 345 blocking diodes and on the shading profile (Alonso-García et al., 1997). Due to the 346 complexity of the problem and the uncertainties in determining accurately the shading 347 and the limitations of the SAPM model it was required the adoption of approximations 348 to explore the capabilities of simple and fast models in modeling these arrays at the 349 different façades.

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351 Two different approaches have been explored to model the array power generation 352 under complex and irregular shading effects. The first one, denoted as Model 1, 353 assumes that each string in the array is working with the maximum current as it would 354 not be affected by shading, and the AC power is finally multiplied by the fraction of the 355 area that is shaded to account for the reduction of power due to shading. The 356 approach of assuming that the power reduction is equal to the shaded array fraction is 357 the most optimistic and represent the minimum limit for power reduction (Martínez-358 Moreno et al., 2010; Masa-Bote and Caamaño-Martín, 2014). The second approach, 359 denoted as Model 2, assumes that the string working current is limited by the shaded 360 modules and then the minimum current of module is assumed for the whole string, 361 and consequently the AC power of the array is not multiplied by any shading factor at 362 all.

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364 Figure 7 shows the daily generation of each array during for the two years modeled. Arrays at west and south façades are generally better modeled than those at east 365 façade. The power output in west and south arrays was predicted with a RMSE of 15% 366 367 and 21%, respectively, in daily basis, and in monthly basis the RMSE was 8% and 12%, 368 respectively. In addition, it can be observed that the uncertainty in estimating the daily 369 production varies along the length of the east façade. The highest differences between 370 experimental and modeled energy production are found in the north part of the east 371 façade (the so called East N array). Figure 8 shows the box plot of the differences

- between hourly experimental power and hourly modeled power with model 2 for each
- 373 array.
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Figure 7. Daily energy production of PV arrays at façades compared to the monitored

379 data.

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Figure 8. Box plot of differences between experimental and modeled power in hourlybasis.

In the case of the three arrays placed at the east façade the modeling results with the
 Model 1 show a general overestimation of the energy throughout the whole year,

389 excepting the case of array East N (placed at the north part of the facade), where the 390 trend is a general and significant underestimation. However, the results of the Model 2 show higher agreement with the experimental data in arrays East S and East Mid, but 391 392 larger underestimations of the output power in array East N during spring and 393 summer. The Model 2 approach has more physical meaning since the shaded modules 394 limit the final current in the string they form part of, and thus a better performance 395 was expected. However, the large uncertainties in these arrays at the east façade 396 evidence the uncertainties in the shading determination due to irregular and changing 397 shading conditions produced by the surrounding trees.

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399 Therefore, this apparently opposite behavior in the predictions of arrays placed at the 400 same facade can be only explained by the different shading modeled along the year, its 401 dynamics and variability, and the impact on the challenging conditions imposed to the 402 array. Thus, the irregular and dynamic conditions of the shading caused by the 403 deciduous trees in front of the east facade make it quite difficult to model accurately 404 the arrays generation by using simple performance models as SAPM. In addition to the 405 propagation of the initial uncertainty of solar radiation components derived from a 406 satellite model, one even most important contributor to the uncertainty is the impact of the limitations in the DSM obtained from LIDAR information. Thus, the information 407 408 in the digital model corresponds to a steady picture of the heights of surrounding 409 objects. Figure 9 shows a picture of the whole east façade in a summer morning where 410 irregular characteristics of the shading can be clearly observed. As can be seen in the 411 picture in front of the east-north facade there is a dry tree without leaves that would 412 explain the underestimation of the energy generated by the array East N. Thus, 413 according to the DSM there is a large tree there, which implies a tall obstacle to the 414 incoming solar irradiance while the actual situation is different. That tree is actually 415 rather transparent to the incoming solar irradiance and the underestimation observed 416 in the calculation is due to erroneous computation of the shading in that part of the 417 building. In addition, in the DSM it can be observed two additional trees at the north-418 east corner of the building that no longer exist (see and compare figure 4 and the 419 picture in figure 9). Indeed, the trees shown in the east-north corner of the building 420 were removed before the installation of the PV modules in the building façades, 421 indicating that the LIDAR information available for the area of study is not updated to 422 the show the refurbishment works performed in the building in 2016. In addition, 423 figure 10 illustrates the shadow induced by the trees, modeled from the DSM data, for 424 three different hours in a single day, where it can be appreciated the irregular shapes 425 of the shadows.



Figure 9. Irregular shading on the east facade caused by trees in a summer morning.



Figure 10. Computed shadows on east façade for three different hours (12:00, 15:00

and 18:00) on a 15th may 2018.

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5. Conclusions

444 Detailed modeling of PV generation at the façades of a building in urban environment requires 445 of both time series of solar irradiance components with good quality and high resolution 446 information on the morphology of the environment to allow shadow casting estimates. There 447 are several open databases of solar radiation data derived from satellite imagery that can be 448 effectively used for that purpose. In addition, the urban morphology can be obtained from 449 LIDAR data to create DSM at high resolution with the heights of buildings, canopies, trees and 450 other structures. This work presents a methodology for modeling PV generation on building 451 façades based entirely on open and free data and methods available. Solar resource basic 452 input consisted of time series of the solar radiation components, in hourly basis, supplied by 453 CAMS Radiation Service for two years (2017 and 2018). Open GIS tools and LIDAR data have 454 been used to create a DSM of a selected area in the university campus of Madrid. Shading and 455 sky view factor have been then computed, from the DSM, for the façades of a selected building 456 in the area of study, where five small PV arrays are installed in façades west, south and east, 457 and monitored. Thus, detailed estimations of incident solar irradiance at each point of every 458 façade are performed by combining shading and SVF parameters with Perez transposition 459 model. Finally, modeling of PV generation of each array was performed by using the SAPM 460 model implemented in PV lib open tool. The methodology presented here thus is aimed at 461 proving that by using free public data and models it is possible to perform a thorough analysis 462 of the PV generation at a building facade in Madrid City. Notwithstanding the study did not 463 need a priori of satellite derived irradiance, since we has measurements of incident irradiance 464 at three directions, the use of open satellite data allows to remark the potentiality of the 465 methodology for future extension at large scale.

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467 The results of PV modeling at façades shown in this work have proven the benefit of this 468 methodology for facades in buildings. The west and south arrays were modeled with good 469 results. However, challenging boundary conditions regarding large deciduous trees close to the 470 east façade have evidenced large uncertainties and difficulties in proper modeling the PV 471 arrays due to the changes throughout the year of trees opacity. On the other hand, recent 472 changes of removing some trees are not contemplated in the DSM since LIDAR data provides 473 information before 2016 (year of refurbishment of the building and surroundings). In other 474 words the static feature of the DSM limits somehow its use in modeling those facades that 475 might be affected by dynamic changes in the surrounding tress and vegetation. The impact of 476 this dynamic partial shading on the arrays at east facade requires a more detailed analysis and 477 the use of complex models that account better for partial shading effects. Future work 478 motivated from these results will be focused on better modeling the performance of these 479 arrays at east facade under the challenging conditions imposed by the presence of large trees 480 in the surroundings.

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49Z 402	Deferences
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