



Investigating the suitability of GIS and remotely-sensed datasets for photovoltaic modelling on building rooftops

Gawley, D., & McKenzie, P. (2022). Investigating the suitability of GIS and remotely-sensed datasets for photovoltaic modelling on building rooftops. *Energy and Buildings*, 265, 1-14. Article 112083. <https://doi.org/10.1016/j.enbuild.2022.112083>

[Link to publication record in Ulster University Research Portal](#)

Published in:
Energy and Buildings

Publication Status:
Published (in print/issue): 15/06/2022

DOI:
[10.1016/j.enbuild.2022.112083](https://doi.org/10.1016/j.enbuild.2022.112083)

Document Version
Author Accepted version

General rights
Copyright for the publications made accessible via Ulster University's Research Portal is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The Research Portal is Ulster University's institutional repository that provides access to Ulster's research outputs. Every effort has been made to ensure that content in the Research Portal does not infringe any person's rights, or applicable UK laws. If you discover content in the Research Portal that you believe breaches copyright or violates any law, please contact pure-support@ulster.ac.uk.

Title: Investigating the suitability of GIS and remotely-sensed datasets for photovoltaic modelling on building rooftops

Author names and affiliation: David Gawley ^a; Paul McKenzie ^a

^a School of Geography and Environmental Sciences, Ulster University, Cromore Road, Coleraine, Northern Ireland, BT52 1SA.

Corresponding author: Dr Paul McKenzie - sjp.mckenzie@ulster.ac.uk

Abstract (200 words)

Rising energy demands and net-zero targets have led to development and implementation of renewable technologies. Rooftop photovoltaic (PV) solar panels offer a viable solution while minimising complex construction or excessive infrastructure development. However, critical physical factors influence building suitability to maximise cost-benefit requirements. This research adopted a Geographic Information System (GIS) approach to identify building suitability by analysing and comparing Digital Surface Models (DSM) derived from Light Detection and Ranging (LiDAR) and orthophotography data using UK standardised PV formulas. Geospatial workflows processed rooftop features and modelled outputs for solar irradiation, panel type, kWh, CO₂, payback and costs while 3D models and solar web applications were used to validate results. Both models suggested a range of between 14.2 and 15.2 GWh potential for an installed capacity of between 21.1 and 22.3 MW. Residential models met between 62.1% (LiDAR) and 66.6% (orthophotography) of average consumer demand with PV potential exceeding 94% of residential dwellings. LiDAR and orthophotography models had strong agreement with existing PV installations. The methodology can be scaled to a regional level and expanded for larger PV capacity. Moreover, the process can assist policymakers with informed decisions on renewable technologies alongside developments such as Peer to Peer (P2P) solar trading.

22 Graphical abstract



24 Highlights

- LiDAR and orthophotography DSMs were compared for solar modelling.
- High agreement between orthophotography DSM and LiDAR solar modelling outputs.
- DSM modelling outputs were compared to web tools and detailed 3D models.
- 3D models produce detailed roof solar analysis identifying obstructions at roof level.
- Web solar tools overestimate solar irradiance compared to 3D models.

31 Keywords

32 GIS, Solar PV, LiDAR, Digital Surface Model, Solar Irradiation, Renewables.

33 1 Introduction

34 To mitigate the impact of climate change, governments across the world are developing policies that foster an
35 energy transition from fossil fuels to renewable energy sources. Increasing demand for energy has encouraged
36 the technological development and promotion of sustainable and reliable energy sources (Gielen *et al.*, 2019).
37 Furthermore, a move away from fossil fuels is associated with better air quality (Mac Kinnon *et al.*, 2018),
38 reduced energy prices (Jacobson *et al.*, 2017) and energy security (Escribano *et al.*, 2013). Transitions in energy
39 systems include solar PV in China (Huang *et al.*, 2019), district heating in Denmark and heat pumps in Finland
40 (Sovacool and Martiskainen, 2020). Approximately 25% of the world's electricity is sourced via clean energy,
41 yet the shift is too slow to meet net zero targets (Gielen *et al.*, 2019). While wind is a significant contributor to
42 renewable electricity in the UK and Ireland (Brodny and Tutak, 2020), solar PV has grown in popularity as it can
43 be retrofitted to homes and offers financial rewards for their installation (Chesser *et al.*, 2018) while also reducing
44 carbon emissions (Liu *et al.*, 2019). The scientific advancement of PV is growing (Kausika *et al.*, 2015) and a
45 reduction in PV costs has encouraged an increase in solar panel fittings in the UK (Balta-Ozkan *et al.*, 2015).
46 The price of homeowner solar technology has fallen since 2008 (Lloyd, 2018), with an average 4 kWp system
47 costing around £6,856 to install (Green Business Watch, 2019).

48 Solar renewables take the form of PV panels which harness radiation from the sun using photovoltaic cells.
49 Typical installations include building facades, large sites and, commonly for homeowners, at roof level. At
50 homeowner level, panels are measured in kilowatt peak (kWp) with the smallest system at 1 kWp (Palmer *et al.*, 2018) and an upper threshold (for UK domestic properties) at 4 kWp (McKenna *et al.*, 2018). Panels do not
51 require direct sunlight and can operate in overcast conditions, albeit with diminished performance
52 (Microgeneration Certification Scheme, 2020). Surplus electricity can be sold back to the grid, providing a
53 revenue stream for the household. Therefore, a viable return on investment is dependent on the system rating,
54 homeowner electricity usage and amount of exported electricity (Energy Saving Trust, 2020a).

56 While solar PV represents a significant form of renewable energy, suitable sites and buildings must be selected
57 to ensure a feasible return on investment. The ability to make informed decisions on PV suitability is critical for
58 property owners, network suppliers and strategic outcomes (Boz *et al.*, 2015). A roof's feasibility for solar panels
59 can involve physical inspections of the building by solar specialists, although this is inappropriate for large scale
60 applications (Brumen *et al.*, 2014). Homeowners can calculate solar potential by providing property data to
61 websites such as the European Commission Photovoltaic Geographic Information System EU PVGIS (2019)
62 and the Energy Saving Trust (2020b). While these tools consider the regional and technical aspects entered by

63 the individual, they are on a building by building basis and depend on homeowner proactivity. Developing a
64 system that highlights potential solar energy generation without homeowner data could incentivise homeowners,
65 or local councils, to install solar PV panels on roof structures. Geospatial technologies and remotely sensed
66 datasets offer considerable potential to identify suitable sites across regional scales (Martín *et al.*, 2015).

67 1.1 GIS and Photogrammetry

68 Geographic Information Systems (GIS) is technology that connects location and attributes, which facilitates
69 spatial investigation, data capture, presentation and analysis (Goodchild, 2009). Photogrammetry techniques,
70 such as Light Detection and Ranging (LiDAR) and orthoimagery, can be used to generate 3D models at
71 individual building level from which solar capacity can be quantified in a GIS (Palmer *et al.*, 2016; Buffat *et al.*,
72 2018; Moudrý *et al.*, 2019).

73 Kausika *et al.* (2015) analysed 0.5m LiDAR data to estimate PV potential in Apeldoorn, the Netherlands, which
74 consisted of mostly residential buildings. The study identified 'viable' and 'partial' regions of roofs that exceeded
75 the city's electricity requirements. However, total capacity assumed that 100% of the classified usable area
76 would support PV. Kodysh *et al.* (2013) used 1.0m LiDAR to identify optimal roof positions for PV for 212,000
77 buildings in Knox County, Tennessee. Within the UK, Jacques *et al.* (2014) developed a scalable procedure
78 using 2m LiDAR to quantify solar potential across 75,000 roof types in Leeds. The model had an estimated
79 accuracy of 81% and could be used to estimate annual yield for kWh per kWp and cumulative GWh. While the
80 studies by Kodysh *et al.* (2013) and Jacques *et al.* (2014) clearly indicate the potential of 3D models, they did
81 not calculate panel outputs, payback or potential CO₂ savings per building. While LiDAR is effective, other forms
82 of DSM data, such as orthophotography produced data, have been used to model PV potential.
83 Orthophotography has a rapid turnaround at reduced costs and is popular with National Mapping Agencies
84 (Rabiu and Wariri, 2014). Agugiaro *et al.* (2012) compared 1m LiDAR and 50cm orthophotography across 1250
85 buildings in Italy and found that orthophotography DSMs outperformed LiDAR in mapping roof features, thus
86 yielding reliable solar results at building level. While other research (e.g. Moudrý *et al.*, 2019) identifies that
87 high-resolution building models offer only marginal gains in predicting solar potential, there is a clear need for
88 further research in the potential of high-resolution 3D models.

89 Roof suitability depends on several factors, including appropriate adequate solar energy, panel orientation,
90 optimal slope position and impact of shadowing (Centre for Alternative Technology, 2020). While different
91 techniques exist to calculate PV potential at roof level from web tools, this is often done on an individual building

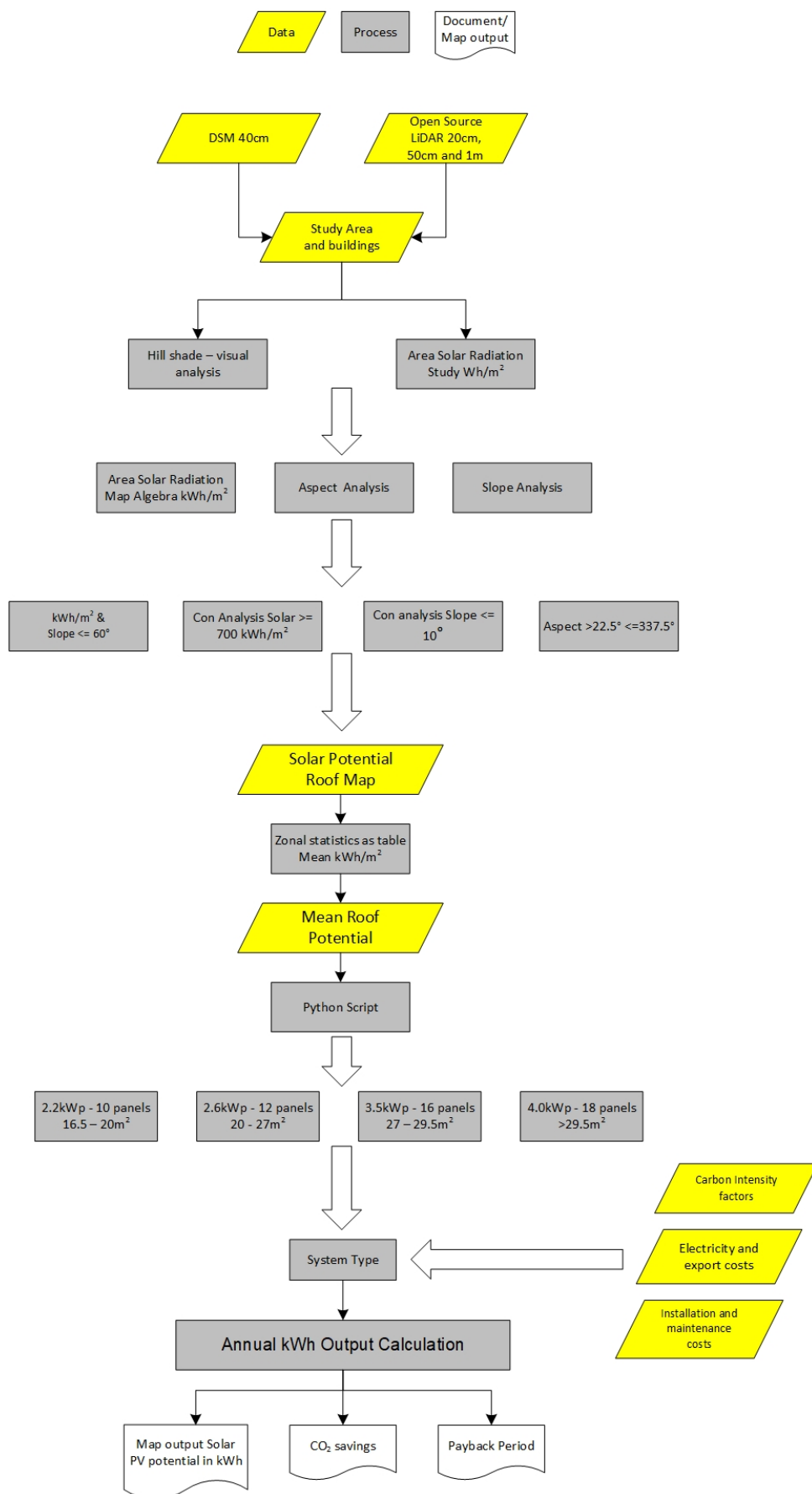
level which is difficult to replicate across large spatial scales (Kodysh *et al.*, 2013). GIS workflows and photogrammetry can rapidly identify solar PV potential across large spatial scales (Melius *et al.*, 2013). These models can then be used by homeowners, local councils or government agencies to identify areas that have maximum potential for solar PV installations (Jakubiec and Reinhart, 2013).

This study compares LiDAR and orthophotography DSM models for the identification of suitable buildings for solar PV panels for several study areas in Northern Ireland. Northern Ireland's renewable energy generation has increased annually since 2010 with green energy production at 47.7% (Northern Ireland Statistics and Research Agency (NISRA) and Department for the Economy, 2020). Of this 47.7%, renewables are mostly Wind (84.8%), followed by Biogas (5.4%) and Biomass (4.0%) with PV only representing (3.6%) above a smaller amount of Landfill Gas (1.6%) and other solutions (0.6%). However, there was a notable expansion in the official number of PV sites from 246 connections in 2010 to 24,662 in 2020, including small scale residential (Department for Business, Energy and Industrial Strategy, 2020). Using rural and urban study areas, the specific objectives of this study were to (i) develop a GIS PV modelling process for roof structures to compare LiDAR and orthophotography; (ii) develop a model output including PV potential, annual yield in kWh, CO₂ savings, and payback period per building and; (iii) compare the results from the remotely-sensed datasets to UK web-based methods of calculation and modelled building samples.

2 Methodology

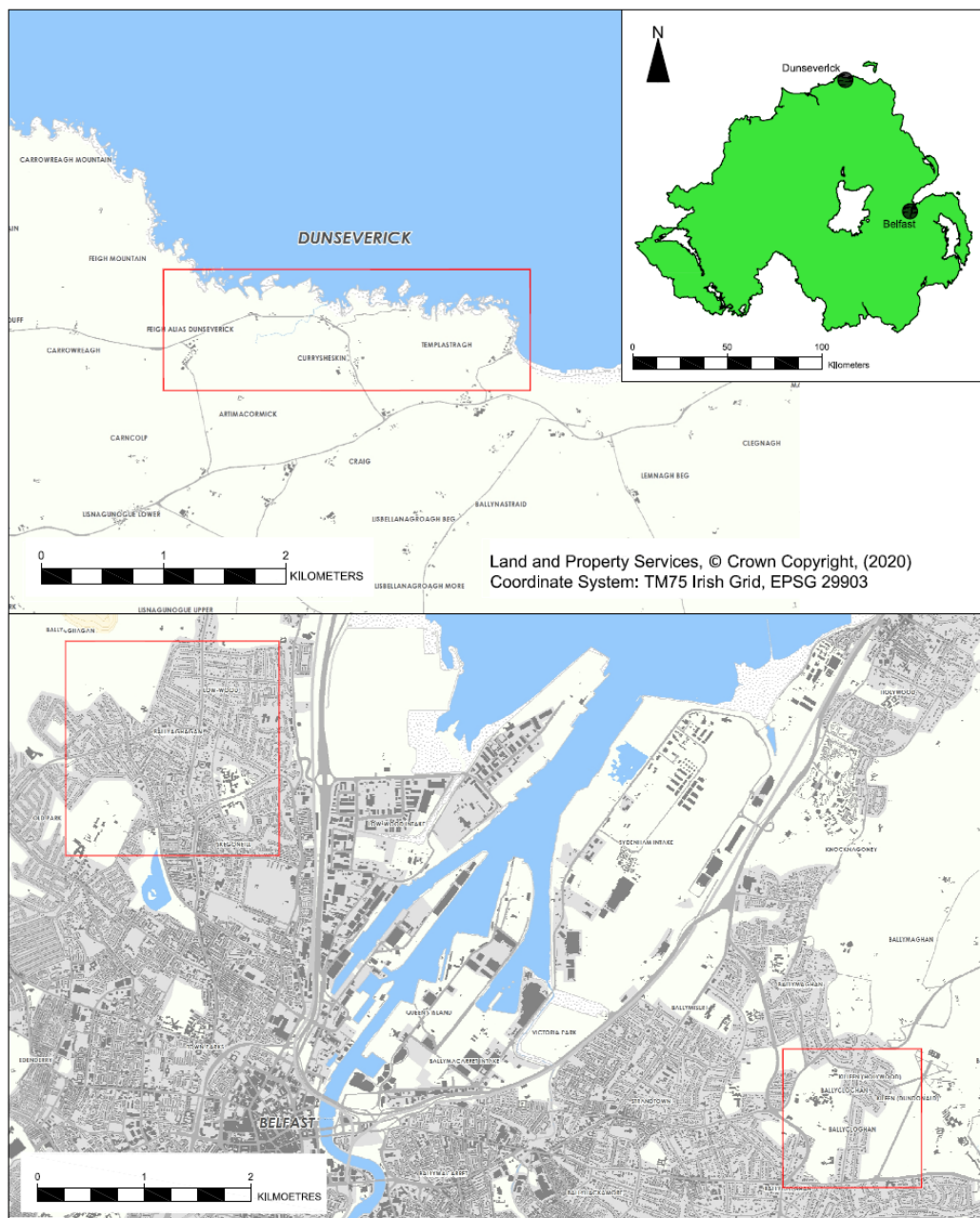
2.1 Overview

The research applied raster spatial analysis workflows in ArcGIS to derive solar potential from LiDAR, and national mapping DSMs at roof level. The conditional analysis factored roof pitch, building orientation and minimum threshold to identify a suitable panel type and averaged yearly solar irradiation value in kWh/m². UK government approved formulas were adjusted and applied to each building to determine kWh, CO₂ savings and payback. For validation and assessment of the procedure, three properties were identified to generate Revit 3D models and compute estimated solar potential. The DSM produced outputs were compared to the 3D models and standardised PV websites by entering data related to the specific building. Figure 1 illustrates the ArcGIS workflow and analysis.



120 2.2 Study Areas

121 DSM datasets are available across Northern Ireland and are provided by Land and Property Services at 40cm
122 resolution (LPS, 2018c) yet LiDAR is restricted to open source provision. LiDAR data at 1m resolution was set
123 as the upper threshold for acceptable GIS PV studies (Kodysh *et al.*, 2013; Palmer *et al.*, 2018). The study area
124 had two locations in Belfast and the third location in Dunseverick (Figure 2).



126 Figure 2: Study data regions in North Belfast, East Belfast and Dunseverick.

128 The main building types in each study area were residential dwellings while some large buildings (e.g. schools)
129 were present in the Belfast study areas.

130 2.3 Solar Irradiance Modelling

131 To estimate PV potential in kWh, solar irradiation is required by determining the available roof area and structure
132 (Melius *et al.*, 2013) which can be generated from remotely sensed data (Hofierka and Zlocha, 2012; Palmer *et al.*, 2018). This study's rooftop solar calculation builds on ubiquitous geospatial computing principles of DSM
133 assessment for irradiation in context to pitch, azimuth and external building envelope (Boz *et al.*, 2015; Song *et al.*, 2018). The research encompasses ESRI (2017) solar calculation principles and Khanna (2020) technical
134 workflows adopted by NVRC (Khan, 2017). The procedure calculated yearly irradiation from the DSM building
135 footprint, isolating regions based on aspect, roof slope and minimum criteria, producing an output per building.
136 Further calculations were rationalised for UK suitability.

139 2.4 Technical Workflows

140 Each dataset was edited and cropped to the extent of the study regions. Solar area analysis in ArcGIS uses
141 direct and diffuse radiation (ESRI, 2017) and considers detailed roof arrangements from the terrain (Chow *et al.*, 2014). The solar area radiation settings were set for a year based on the latitude of each study area with a
142 14-day hourly interval. A sky size of 200 was appropriate with 32 calculation directions, eight zenith and azimuth
143 divisions and a z factor of 1. A vector building outline was used as an input mask to calculate the yearly
144 irradiation on the surface models based on the Irish Grid coordinate system (LPS, 2019). The mask ensured
145 the outputs were constrained to the building whilst still accounting for roof obstacles and terrain. The process
146 produced irradiation values based on yearly calculations in Wh/m² which were adjusted to kWh/m² (Khanna,
147 2020).

149 A range of permissible roof slopes have been identified ranging from 30° (Energy Saving Trust, 2014) to 60°
150 (Margolis *et al.*, 2017; Palmer *et al.*, 2018) with prime angles between 39-40° in NI (Invest NI, 2013). Based on
151 the evidence, this study executed conditional raster analysis on the solar outputs concerning building pitch,
152 removing slopes greater than 60°. A review of the modelling scenarios determined that setting a threshold of
153 700 kWh/m² (Figure 1) predominately removed north-facing roofs. Moreover, solar irradiation below this value
154 would be economically unviable, particularly for smaller PV installations without significant financial incentives.
155 A minimum threshold of 700 kWh/m² was used as a baseline (Cole *et al.*, 2016) with lower irradiation values
156 removed although this accounted for the removal of a very small percentage of buildings (<5%). Additional

conditional exclusions were executed on orientations between 337.5° and 22.5°. Exceptions were applied to roofs less than 10° (Boz *et al.*, 2015; Khanna, 2020) and over 700 kWh/m², which could have adjustable panels installed.

Identifying the appropriate aspect is important in determining solar PV potential with north considered as low potential (Kouhestani *et al.*, 2018; Tiwari *et al.*, 2020). The output models were pooled using zonal statistics to determine an overall yearly average irradiation value (Groppi *et al.*, 2018; Kouhestani *et al.*, 2018) which produced an average kWh/m² per building.

Studies in Europe have used 1kWp (Groppi *et al.*, 2018; Palmer *et al.*, 2018), while 4kWp represents a typical UK configuration (Ofgem, 2020). PV panel formation and numbers vary depending on the available rooftop area and suitability, which influences the output ranging from a minimum of 1.3 kWp to typical 4 kWp (Energy Saving Trust, 2015). A Python script was developed to calculate panel size and assess suitability for 1.3 kWp to 4 kWp based on the Energy Saving Trust (2015) roof areas from 9.6m² to 29.5m² (Table 1). Estimated installation costs were accumulated from a review of the Energy Saving Trust costings combined with a review of UK suppliers and the Department for Business, Energy and Industrial Strategy (2019) figures for micro-PV systems per kWp (Table 1).

172

Table 1: Panel sizing guide adopted in the Python script to determine the appropriate kWp. Panels based on the Energy Saving Trust (2015) sizing guide, which was adjusted to consider 20% of regions not usable.

Roof area (m ²)	kWp	Estimated Panels	Estimated cost including VAT
>0<9.6	Not suitable for Solar	-	-
>9.6<16.5	1.3	6	£2095
>16.5<20	2.2	10	£3766
>20<27	2.6	12	£4360
>27<29.5	3.5	16	£5769
>29.5	4	18	£6376

175

176

In the UK, based on the Standard Assessment Procedure (SAP) guidelines, the Building Research Establishment (BRE) uses the following formula for annual kWh electricity production for PV:

$$\text{Electricity Production in kWh/Year} = 0.8 \times \text{kWp} \times S \times Z_{pv} \text{ (BRE, 2014, p.86)}$$

179

180 Where kWp is the highest output of the panel, 0.8 is an empirical performance factor, S is yearly irradiation in
181 kWh/m² available from climate charts which applies to the pitch and orientation. Zpv is a shading ratio from four
182 variables ranging from no shadowing (1.0) to a high impact of shadowing (0.5). The Energy Saving Trust adopts
183 the formula, yet the user determines the shading impact 'S' based on their observations of obstructions on the
184 property. In contrast, the Microgeneration Certification Scheme (MCS) uses the following formula to calculate
185 yearly kWh:

186
$$\text{Annual AC Output (kWh)} = \text{kWp} \times \text{Kk} \times \text{SF (MCS, 2012, p.59)}$$

187 Where kWp is panel output, SF is the shading ratio, and Kk is the total kWh/kWp available from climate-SAF-
188 PVGIS charts based on pitch, orientation and pre-factored performance values of 0.8. BRE (2016) compared
189 the MCS and SAP methodology and concluded that the equations are the same. However, shading is a foremost
190 negative contributor on performance with MCS yielding a more comprehensive approximation due to the sun
191 tracking charts (BRE, 2016). Application of the SAP process using the shading factor tables can reduce the total
192 yearly kWh by 50% (BRE, 2014). Furthermore, Levinson *et al.* (2009) emphasise the need for an apt
193 methodology in solar studies due to the impact of tree canopies, structures and other external features which
194 could degrade results. The geospatial workflow in ArcGIS provides comprehensive spatial processing on
195 remotely-sensed data, factoring elevation, location, and shadowing effects (ESRI, 2017). Therefore, the BRE
196 Zpv and MCS SF shading factors were excluded (i.e. considered as 1.0) as ArcGIS calculated the impact of
197 shading. The overall performance factor of 0.8 was retained deriving the following formula for the project
198 electricity output:

199
$$\text{Annual kWh output} = \text{kWp (ArcGIS)}_a \times \text{S (ArcGIS)}_b \times 0.8 \text{ performance ratio}$$

200 _a kWp, derived by a Python script based on suitable roof areas for 1.3, 2.2, 2.6, 3.5 and 4 kWp.

201 _b Yearly solar irradiation (kWh/m²) derived from ArcGIS zonal statistics calculated workflows.

202

203 PV solutions deliver a green option, and the fabrication process can yield a carbon payback within three years
204 (Centre for Alternative Technology, 2020). CO₂ savings were calculated based on the Department of Agriculture,
205 Environment and Rural Affairs (DAERA) carbon intensity factors at 406g/kWh (DAERA, 2019) with a deduction
206 of three years to accommodate emissions from the manufacturing process. The following calculation was
207 applied, assuming a 25-year lifespan:

208 CO_2 Tonnes saved = Calculated PV Electricity Production in kWh/Year x 406×10^{-6} T/kWh x 22 years

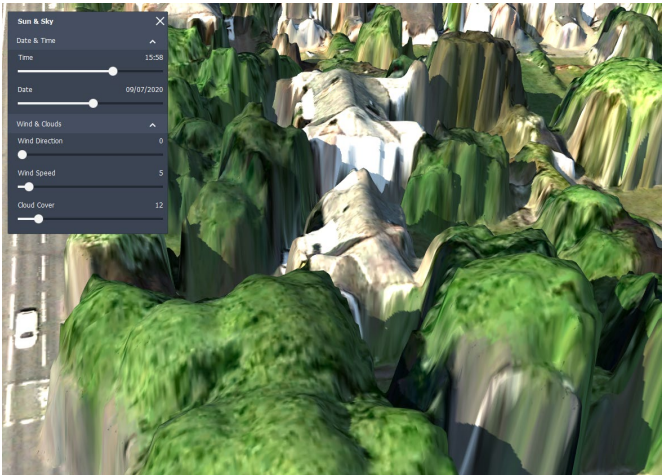
209 There is a challenge in estimating how PV saves electricity in the UK as there is a variance in household
210 consumption and export amounts to the grid (McKenna *et al.*, 2019) with estimates of consumption between
211 37% (McKenna *et al.*, 2018) and 55% (Action Renewables, 2020). Based on previous studies, this research
212 adopted 50% as the operating figure. The study regions presented a small number of commercial properties
213 and factors for businesses were excluded from different PV assessment models. Payback periods required tariff
214 export rates and standard electricity consumption rates from Power NI (2020a) at £0.051 and £0.1874 (Power
215 NI, 2020b), respectively. PV technology is relatively maintenance-free; however, a typical planned cost of £800
216 should be allocated for inverter replacement (Centre for Alternative Technology, 2020). The study payback
217 equation was based on Invest NI's (2013) formula with the removal of expired renewable credits (Department
218 for the Economy, 2020), and inclusive inverter costs:

219 Simple Pay Back = (Capital Cost + Inverter replacement) / (Replaced power value + Export value)

220 The payback and the CO₂ calculations were performed on the output tables in ArcGIS and spatially joined to
221 the vector building data with all other outputs.

222 **2.5 Methodology Validation**

223 A validation process was developed to verify the outputs of the DSM workflows. Autodesk InfraWorks was used
224 by inputting the DSM into a model with draped orthophotography creating an aggregated 3D output. The time
225 and date could be adjusted in real-time with spatial correctness for sun and sky to identify regions which had
226 unexpected low results for south-facing properties (Figure 3).



227

Figure 3: Left – solar calculation for a south-facing roof with low potential due to the tree canopy. Right illustrates the DSM in Autodesk InfraWorks. The time of day and year can be adjusted to review the shadow effect and verify any negative impact from surrounding vegetation.

As the data had temporal and resolution differences, a review of the surfaces for any distinguishing changes was appropriate (Gehrke *et al.*, 2010; Alganci *et al.*, 2018). This was achieved at two levels by reviewing overlaid cross and long sections of the data in Autodesk Civil 3D and by creating differences in the LiDAR and DSM datasets using map algebra tools in ArcGIS.

2.6 Solar Model Verification

Two approaches were adopted to verify the solar DSM calculated outputs: firstly, a 3D model was developed in Autodesk Revit and analysed using Autodesk Insight, and secondly, building data were validated on PV websites. Prior to constructing the 3D models and applying web-based calculations, a property from each study region was identified based on typical household installations of 4 kWp (Ofgem, 2020). For a fair comparison, the selection of the buildings confirmed that temporal disparities in the datasets did not exist due to changes in the surrounding environment caused by vegetation or structure. The building measurements were constructed from an external site verification, Google street maps and a photograph raster-to-vector process using Civil 3D. The process generated known dimensions of the building elevations, roof pitch and other measurements such as chimney details. The dimensions were used to develop parametric models in Autodesk Revit.

PV web-based evaluation tools were reviewed to authenticate the ArcGIS and Revit outputs namely NREL PVWatts (2020), EU PVGIS (2019) and the Energy Saving Trust (2020b). The data related to the three sample properties for building location, orientation and roof slope were manually entered with default efficiency losses.

2.7 Analysis

IBM SPSS V25 tests for Q-Q plots, Kolmogorov-Smirnov and Shapiro-Wilk's were performed to identify if the solar PV estimates were normally distributed. The results indicated the data were non-parametric and not normally distributed; therefore, Wilcoxon tests were applied to compare the LiDAR and DSM solar irradiation outputs for the three different resolutions.

3 Results

Table 2 summaries the classification of PV modelling of 9436 buildings over three regions. 76.3% (LiDAR) and 77.2% (DSM) of all buildings were identified as being suitable within the banding with a high level of agreement between the LiDAR and DSM data.

258 *Table 2: Summary of analysed buildings and corresponding panel type.*

Panel Type/Region	North Belfast (8605 buildings)		East Belfast (671 buildings)		Dunseverick (160 buildings)	
	LiDAR	DSM	LiDAR	DSM	LiDAR	DSM
Failed to meet modelling criteria	308	292	64	48	6	6
No Panel	1700	1643	135	147	23	16
1.3 kWp	1303	1036	59	71	25	21
2.2 kWp	773	600	30	21	13	11
2.6 kWp	1578	1443	39	37	26	22
3.5 kWp	414	523	9	9	7	3
4 kWp	2529	3068	335	338	60	81
Total buildings with potential 1.3-4 kWp	6597	6670	472	476	131	138

259

260 4 kWp was the primary system for both data types while 3.5 kWp was the minority configuration with an average
 261 of 22.9% of buildings in both Belfast regions failing to meet the minimum PV suitability. The modelled LiDAR
 262 data had a lower capacity than the modelled DSM data, both in terms of GWh capacity and buildings satisfying
 263 PV modelling criteria. However, there is a strong agreement between the LiDAR and DSM model outputs,
 264 particularly for East Belfast (Table 3).

265 *Table 3: Summary of GWh for 1.3 – 4 kWp systems calculated from LiDAR and DSM datasets.*

Region/Output	Collective yearly GWh capacity up to 4 kWp	Difference GWh LiDAR - DSM	Number of potential buildings	Difference Buildings LiDAR - DSM
Belfast LiDAR	12.90	-7.21%	6597	-1.11%
Belfast DSM	13.83		6670	
East Belfast LiDAR	1.059	-0.50%	472	-0.85%
East Belfast DSM	1.064		476	
Dunseverick LiDAR	0.26	-11.54%	131	-5.34%
Dunseverick DSM	0.29		138	

266

267 Variation in LiDAR and DSM irradiation values were relatively low across all three study areas (Table 4) with
 268 North Belfast showing the highest variation (0.55%) and East Belfast showing lowest variation (-0.25%). Again,
 269 North Belfast had the highest mean difference in kWh while East Belfast had the lowest scores. Despite East
 270 Belfast having the lowest average irradiation, lifetime CO₂ and kWh/year were the highest compared to all
 271 regions. The elevated CO₂ and kWh for East Belfast was associated with a high proportion of 4 kWp panels for
 272 both datasets at 71%. An appraisal of the carbon footprint signified comparable totals and saving in CO₂
 273 emissions over 25 years of 127,028T CO₂ (LiDAR) and 135,681T CO₂ (DSM). Payback periods ranged from
 274 19.7 (North Belfast) to 32.6 (East Belfast).

275 Table 4: Solar irradiation, kWh, CO₂ 25-year saving, and payback calculated from LiDAR and DSM models.

Output/Dataset	North Belfast				East Belfast				Dunseverick			
	LiDAR	DSM	Diff	%	LiDAR	DSM	Diff	%	LiDAR	DSM	Diff	%
Average kWh/m ²	833.9	829.3	4.6	0.55%	804.9	806.9	-2	-0.25%	820.6	823.3	-2.7	-0.33%
Average building kWh	1956	2074	-118	-6.03%	2244	2234	10	0.45%	1990	2123	-133	-6.68%
Total CO ₂ saved 25 Years (Tonnes)	115238	123564	-8326	-7.23%	9462	9500	-38	-0.40%	2328	2617	-289.4	-12.43%
Average CO ₂ saved 25 Years (Tonnes)	17.5	18.52	-1.02	-5.83%	20.04	19.96	0.08	0.40%	17.8	19	-1.2	-6.74%
Average payback (years)	24.5	24.2	0.3	1.22%	24.3	24.2	0.1	0.41%	24.8	24.4	0.4	1.61%
Minimum payback (years)	19.7	19.7	0	0.00%	20.5	20.5	0	0.00%	20.3	20.7	-0.4	-1.97%
Maximum payback (years)	32.4	32.5	0.1	-0.31%	32.6	32.4	0.2	0.61%	31.5	31.1	0.4	1.27%

276

277 There were very few commercial, recreational or religious buildings as residential dwellings made up 66.4%
278 and general buildings 30.3% of all regions. General buildings (e.g. garages) were prevalent under the ‘no panel’
279 category with many of these buildings having small roof areas. Residential dwellings represented most
280 properties in North and East Belfast. Isolating residential buildings for 1.3–4 kWp detected a 94%+ and 88%+
281 suitability for North and East Belfast respectively for LiDAR and DSM data. Dunseverick is coastal and most
282 buildings were classified as general, predominately due to farm structures. The residential analysis of
283 Dunseverick determined PV suitability at 96.61% (LiDAR) and 98.31% (DSM), albeit based on a lower number
284 of observations.

285 **3.1 Non-Parametric Testing**

286 Wilcoxon signed-rank tests were applied to evaluate any statistically significant differences in the modelled
287 outputs. While there were significant differences between the modelled DSM and LiDAR data, most variables
288 in East Belfast were not significantly different apart from solar irradiance and solar area. Significant differences
289 occurred in North Belfast and Dunseverick. The results suggest that the DSM data were aligned with the high-
290 resolution 0.2m LiDAR data for solar analysis as were the calculated outputs of the lower resolution (1.0m) data
291 for East Belfast (Table 5).

292

293 *Table 5: Wilcoxon signed-rank test results for North Belfast, East Belfast and Dunseverick.*

	North Belfast		East Belfast		Dunseverick	
	0.5m LiDAR, 0.4m DSM		1.0m LiDAR, 0.4m DSM		0.2m LiDAR, 0.4m DSM	
Test result	Z	Sig. (2-tailed)	Z	Sig. (2-tailed)	Z	Sig. (2-tailed)
Solar irradiation	-18.713	0.00	-3.888	0.00	-0.999	0.318
kWh	-18.327	0.00	-0.629	0.53	-5.366	0.000
Panel type	-23.141	0.00	-0.070	0.94	-4.730	0.000
Payback	-15.296	0.00	-1.116	0.26	-4.730	0.000
CO ₂	-18.327	0.00	-0.629	0.53	-4.832	0.000
Solar area	-40.966	0.00	-4.442	0.00	-8.895	0.000

295 3.2 3D Models and PV Web Analysis

296 Constructing the 3D models aided in isolating pockets of lower solar energy. However, any deviations in solar
 297 outputs were due to obstructions at roof level and not the surrounding terrain as this was not modelled. The
 298 main roof surfaces produced uniformly distributed peak isolation values of 928 kWh/m² (North Belfast), 957
 299 kWh/m² (East Belfast), and 969 kWh/m² (Dunseverick).

300 PV Websites observed higher solar irradiation values over the LOD models and DSM outputs exceeding 1000
 301 kWh/m² except for PV Watts (East Belfast). In contrast, none of the 9436 buildings modelled in ArcGIS reached
 302 this threshold. Dunseverick's 3D model recorded a low value as it was segmented over two roofs. Autodesk
 303 Insights recorded the 3D model's irradiation as 781.27 kWh/m², with an average on the primary roof at 951.5
 304 kWh/m² and the secondary roof at 624.54 kWh/m². If a proportionate approach were executed based on the
 305 average surface isolation value and corresponding roof surface area, a figure of approximately 814 kWh/m²
 306 would be substituted. Not all PV websites had the ability to estimate CO₂, annual benefit or installation costs;
 307 therefore, kWh and irradiation were the only comparable variables. kWh was inflated for the LOD models as the
 308 calculation used a methodology to derive output based on area, solar irradiation and panel efficiency. PVGIS
 309 reported a yearly variation in kWh/m² based on the standard deviation (EU PVGIS, 2020); however, no
 310 adjustment was factored in the kWh calculation (Table 6).

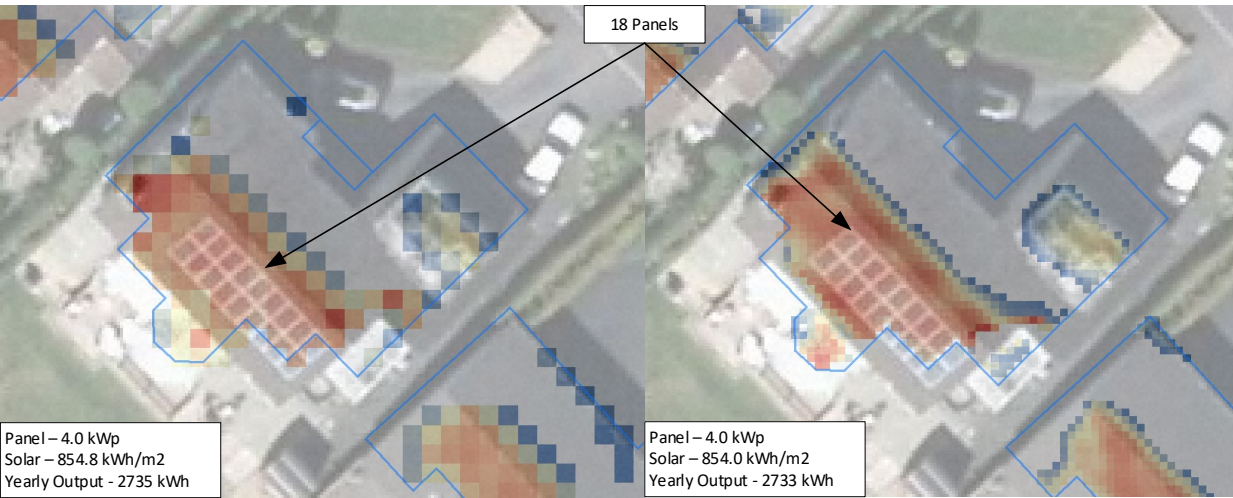
312 Table 6: PV comparison of assessments methods applied to the three sample buildings.

Property	Source	System	CO ₂ (Kg/Year)	Installation Cost (£)	kWh	Annual Benefit (£)	Assessment	Irradiation (kWh/m ²)
BT15, North Belfast	Energy Saving Trust	4 kWp	1036	5970	3375	218.00	SAP 2012	1054.69
	PVWatts	4 kWp	Not calculated		3088	578.00	NREL	1000.79
	EU PVGIS	4 kWp	Not calculated		3275	NA	CM SAF	1074.40
	LiDAR	4 kWp	1094	6376	3063	365.11	ArcMAP/MCS	957.27
	DSM	4 kWp	1080	6376	3022	360.22	ArcMAP/MCS	944.24
	LOD200 Revit	Not Calculated			4423	840.00	Perez	920.40
BT57, Dunseverick	Energy Saving Trust	4 kWp	1047	5970	3412	220.00	SAP 2012	1066.25
	PVWatts	4 kWp	Not calculated		3240	608.00	NREL	1037.31
	EU PVGIS	4 kWp	Not calculated		3177	NA	CM SAF	1046.70
	LiDAR	4 kWp	1006	6376	2817	335.79	ArcMAP/MCS	880.30
	DSM	4 kWp	994	6376	2781	331.50	ArcMAP/MCS	869.08
	LOD200 Revit	Not Calculated			4542	863.00	Perez	781.27
BT4, East Belfast	Energy Saving Trust	4 kWp	1020	5970	3324	216.00	SAP 2012	1038.75
	PVWatts	4 kWp	Not calculated		3053	573.00	NREL	989.83
	EU PVGIS	4 kWp	Not calculated		3339	NA	CM SAF	1093.69
	LiDAR	4 kWp	1020	6376	2854	340.20	ArcMAP/MCS	891.79
	DSM	4 kWp	1043	6376	2921	348.18	ArcMAP/MCS	912.68
	LOD200 Revit	Not Calculated			4574	869.00	Perez	928.32

313

314 3.3 Validation

315 Visual verification of installed PV systems identified from the orthophotography corroborates the model outputs
316 and methodology. Several sites were discovered, ranging from larger installations to smaller outhouse
317 arrangements (Figure 4).



318

319 *Figure 4: North Belfast detached house with highly comparable outputs for LiDAR (left), and DSM (Right)*
320 *overlaid on the installation.*

321

322 A comparison in level changes between LiDAR and DSM revealed that the Belfast datasets had substantial
323 fluctuations while Dunseverick had the least difference. The DSM data elevations are closer for the East Belfast
324 data as the mean difference in DSM is 0.22m despite the high outliers. The Dunseverick mean difference was
325 -0.26m, although numerous pitted areas and post-processing of coastal boundaries of the datasets could
326 influence the results (Table 7).

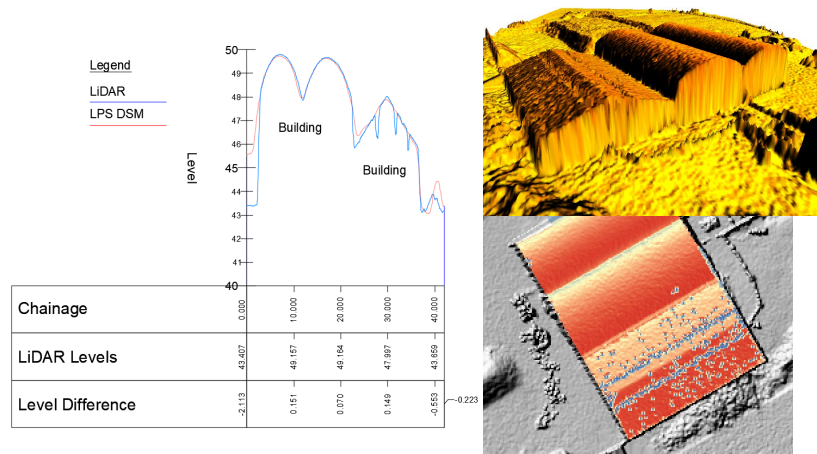
327 *Table 7: LiDAR - DSM statistics for changes in level (m).*

Descriptive/Datasets	North Belfast	East Belfast	Dunseverick
Minimum	-33.60	-33.93	-14.56
Mean	-1.03	0.22	-0.26
Maximum	44.03	37.28	10.29
SD	3.10	3.38	0.55

328

329 A long section examination facilitated a quality review between building profiles. In specific dense locations the
330 50cm LiDAR data for Belfast had a greater difference between detached houses than the DSM. Despite East
331 Belfast's overall mean level difference being 0.22m, a detailed visual inspection indicated a consistent gap in
332 the building profiles of 0.5m. The 40cm DSM proved capable of identifying detailed roof profiles and was well
333 aligned with Dunseverick's LiDAR (Figure 5). Irregularities in the Dunseverick LiDAR data included 'pitted'
334 regions, lowering solar clusters of single-pixel values (Figure 5).

LONGSECTION D-D FARM BUILDINGS ADJACENT TO CAUSEWAY ROAD
SCALE: H 1:500,V 1:100. DATUM: 40.000



D-D - LONGSECTION EAST BELFAST
SCALE: H 1:500,V 1:100. DATUM: 25.000

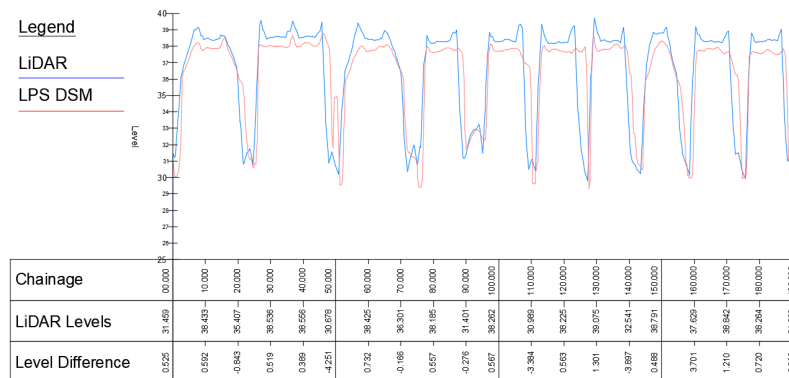


Figure 5: Top: Long section of farm buildings in Dunseverick. Pitted regions in the LiDAR influencing solar results are visible. Bottom: Long section in East Belfast of detached houses with a notable consistent difference in level (LiDAR – DSM) of approximately +0.5m.

The results above suggest a strong agreement between the DSM and the LiDAR model, particularly for the East Belfast study area. The results also suggest significant capacity to install solar PV panels on many residential dwellings across all three study areas.

4 Discussion

This study investigated the extent to which LiDAR and orthophotography produced DSMs could be used to locate solar PV panels on buildings. The study found a high level of agreement between LiDAR models and DSM orthophotography models, suggesting that LiDAR may not be necessary for accurate estimates of PV potential on buildings. Both models identified that approximately 94%+ of all residential buildings could accommodate PV panels between 1.3 kWp to 4 kWp. While panel sizes can be adjusted, this study used a range between 1.3 kWp to 4 kWp which yielded an overall potential of approximately 14.7 GWh/year for a 21.7

350 MW installation. The models calculated a significant potential annual saving of residential CO₂ of approximately
351 5,236 Tonnes based on DAERA (2019) carbon intensity figures. The research and methodology demonstrate
352 that widely available low-cost photogrammetric national mapping data can determine the capacity to install PV
353 panels on rooftops across vast spatial scales derived from government-approved formulae without the need to
354 commission complex and expensive LiDAR studies.

355 4.1 Comparison of LiDAR and Orthophotography Modelled Solar Outputs

356 LiDAR data has been a particularly effective dataset for estimating PV potential on buildings (Kodysh *et al.*,
357 2013; Boz *et al.*, 2015; Kausika *et al.*, 2015) and suitable land (Finn and McKenzie, 2020). However, LiDAR
358 remains costly with elongated timeframes to capture (Nelson and Grubestic, 2020) which could restrict its
359 application in PV site selection. Conversely, aerial photogrammetry has developed significantly over recent
360 years with increased spatial resolution (Pan *et al.*, 2019) along with improved photogrammetric techniques
361 (Rabiu and Waziri, 2014). Furthermore, aerial photogrammetry is often collected on a routine basis by national
362 mapping agencies, thus providing regular updates at lower costs than LiDAR. Aerial photogrammetry offers a
363 distinct advantage over other datasets, such as UAV photogrammetry (Moudry *et al.*, 2019), as it is collected
364 over very large spatial scales in a short timeframe.

365 This study investigated the level of agreement between both LiDAR and DSM photogrammetry to determine if
366 PV estimates were significantly different. Results (Table 5) showed significant differences for North Belfast and
367 Dunseverick yet high agreement for East Belfast. One of the main factors that caused significant differences for
368 North Belfast and Dunseverick was temporal differences in the datasets. Accessing remote sensing data at
369 similar timeframes is challenging, so it is vital to identify constant areas within DSMs for comparison (Alganci *et al.*, 2018). Wong *et al.* (2016) observed the difficulty in processing LiDAR solar analysis due to temporal
370 differences as structures change over time through new developments or building removal. The study relied on
371 the accuracy of the building footprint aligned with DSM. A review of Dunseverick's buildings demonstrated that
372 124 of 160 building footprints matched both DSMs. The remaining buildings presented pitted regions in the
373 LiDAR, or the structure was not aligned with the DSM due to building demolition or construction. This work
374 demonstrates that future studies that seek to analyse multiple datasets should have a verification process by
375 comparing the DSM to building outlines, then eliminating buildings where the DSM does not match both
376 datasets, making the models more comparable.

378 Brumen *et al.* (2014) illustrated the reduction in PV capability due to tall vegetation in proximity to buildings post-
379 analysis. Comparing the North Belfast modelled kWh/m² differences in relation to changes in level verified the
380 positive and negative impact vegetation had on both data models, with several regions presenting extensive
381 changes in structure and tree canopies. The corresponding orthophotography by closest date was overlaid in
382 InfraWORKS with contours to validate the differences. Whilst there was a good agreement between LiDAR and
383 DSM modelled outputs, discrepancies could easily be identified by the changes in mature vegetation growth
384 from the 2006 LiDAR to the 2018 DSM data.

385 Jochem *et al.* (2009) applied transparency factors on LiDAR solar modelling to foliage respecting the natural
386 way of daylight penetration which could be beneficial as the DSM data is more solid in appearance compared
387 to LiDAR. However, the validation process used in this study supports the use of recent data when executing
388 an analysis of vegetation areas prone to growth spurts. The process could consider future growth scenarios
389 (Levinson *et al.*, 2009), yet this is a complicated procedure and issues in this study were only evident in isolated
390 areas.

391 Figure 6 reveals the detail of the 20cm LiDAR on a chimney in the Dunseverick model, which was not
392 identified in the DSM model due to resolution. While this level of detail is valuable, there was only a -1.3%
393 difference between the DSM irradiation and LiDAR. This agreed with Lingfors *et al.* (2017) and Moudrý *et al.*
394 (2019) who both found that lower-resolution models performed well in contrast to higher-resolution models
395 when classifying roof structure faces for PV. Furthermore, Moudrý *et al.* (2019) observed that less than 1m
396 resolution data is not required for dependable solar irradiance values on plain roofs with no or marginal
397 obstructions when comparing an actual PV installation to modelled outputs. This study highlights the value of
398 widely available orthophotography in mapping suitable roofs for PV installations.

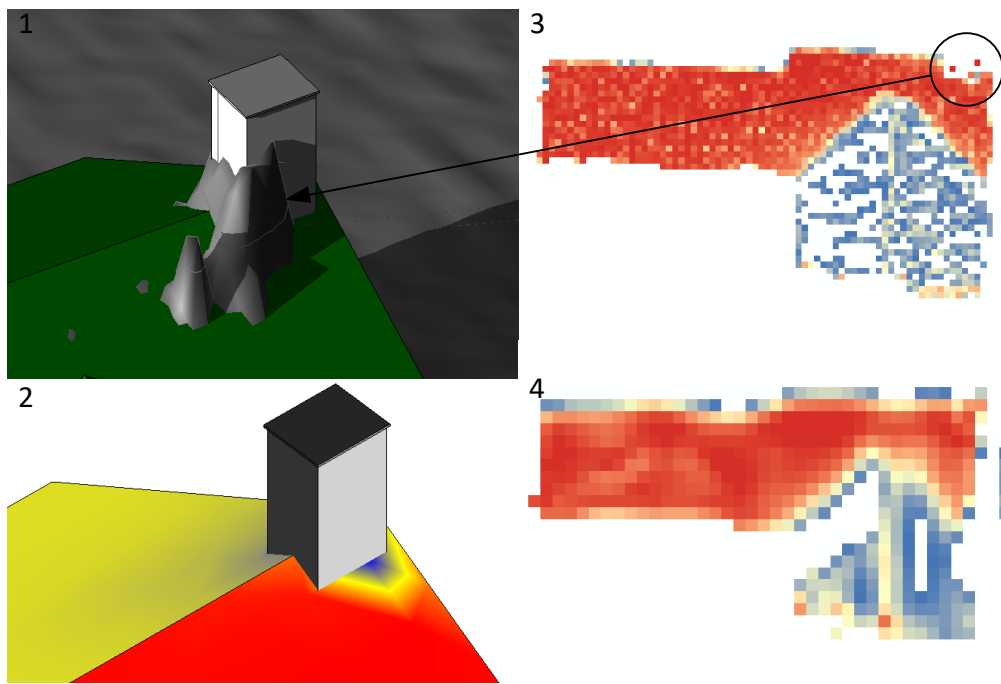


Figure 6: (1) Illustrates the model with LiDAR overlaid. (2) Analysis of the model with low irradiation regions due to the modelled chimney. (3) LiDAR data with the chimney region nearly removed as part of the ArcGIS workflows. (4) DSM does not have the resolution to consider the chimney.

Visual examination of imagery can authenticate existing PV fittings on buildings (Latif *et al.*, 2012; Mainzer *et al.*, 2017). Notwithstanding the limitations in significance testing, and temporal differences in datasets, the confirmation of several solar installations per study area supported the methodology and data agreement for LiDAR and the DSM. Furthermore, verification of long sections compared relatively well to identify roof features from both datasets although the DSM offered advantages over the LiDAR data.

4.2 Estimation of PV Potential, CO₂, Savings and Payback

While other studies have used models to estimate the potential energy that PV could produce, this study provides additional results on cost recovery, CO₂ savings and PV panel sizing based on UK government restrictions. We demonstrate that remotely sensed datasets, such as LiDAR or ortho DSMs, can be successfully used to determine solar PV suitability at the individual household level (Kausika *et al.*, 2015; Wong *et al.*, 2016; Song *et al.*, 2018) or at aggregated census scales (Palmer *et al.*, 2016). While Kausika *et al.* (2015) suggested that surplus electricity could be generated for Apeldoorn, this study, based on UK formulas (MCS, 2012) estimated yearly output of approximately 2,181 kWh/year for suitable residential buildings. The Northern Ireland Authority for Utility Regulation (NIAUR) indicates the average homeowner consumes 3200 kWh/year (NIAUR, 2019), suggesting that solar could generate almost 70% of residential demand which agrees with other studies

419 (Hofierka and Kaňuk, 2009). This is based on current regional restrictions on solar panels which, if relaxed,
420 could further reduce energy costs.

421 The study's 700 kWh/m² threshold assisted in eliminating low regions along with roof pitch and building
422 orientation constraints. Kausiki *et al.* (2015) applied a 70% rule to annual irradiation in the Netherlands,
423 identifying 600 kWh/m² as the lower limit. A similar application to Northern Ireland could improve workflows
424 based on yearly global horizontal irradiation values of 801-1000 kWh/m² (MCS, 2012) which would determine
425 a limit of 561 – 700 kWh/m². A lower limit could elevate panels on borderline categories or promote previously
426 unsuitable buildings (i.e. small outbuildings) to the minimum 1.3 kWp (Boz *et al.*, 2015), thus increasing energy
427 estimates.

428 The second possible improvement is the consideration of contiguous roof areas (Boz *et al.*, 2015; Gagnon *et*
429 *al.*, 2016). PV panels are positioned in arrays at optimal roof positions for maximum performance. Therefore,
430 the spatial process could be enhanced to identify the single largest contiguous area on the roof with zonal
431 statistics applied. Yet, it was noted that many modelled outputs were predominately contiguous when processed
432 with some sporadic pixels.

433 A selection of larger buildings in both Belfast regions calculated a lower kWh/year due to the 4 kWp limit and
434 flat roofs. Moreover, under normal installation conditions, it is expected that panels on flat roofs would be
435 optimised for a suitable angle (Mainzer *et al.*, 2017) generating a higher yearly return. The parameters used in
436 this study mean that none of the study areas meet the NIAUR (2019) estimated yearly average households'
437 electricity consumption of 3200 kWh. However, altering parameters could significantly increase potential
438 power generation from PV. For instance, a 5.3 kWp system in Northern Ireland could generate enough
439 electricity to sustain household demand throughout the spring to summer months (MacIntyre, 2019).

440 Therefore, considering the 4 kWp limit, accommodating a higher system would generate greater opportunity
441 and output provided policy changes would facilitate a change in threshold. Indeed, while calculating the
442 maximum 4kWp for domestic buildings in Belfast, additional roof areas were deemed suitable for PV at 58.5%
443 (DSM) and 54.3% (LiDAR). Applying the extended validated areas would breach current regional restrictions
444 but clearly illustrates the significant potential of solar PV if current policy was changed.

445 While capital costs of solar panels are reducing (Balta-Ozkan *et al.*, 2015) the average project payback for all
446 datasets and regions fell within 25 years with maximum periods extending to 32.6 years and minimum return
447 on investment at 19.7 years. The Northern Ireland Renewables Obligation (NIRO) ceased in March 2017

(Department for the Economy, 2020) which allocated payments for every MWh of electricity generated regardless if consumed or exported (Green Business Watch, 2014). Current Renewable Obligation Certificates (ROC) payments are available for panels installed within the qualifying period (Department for the Economy, 2020). Eligible panels falling within the timeframe which are valid to collect ROC credits receive an additional variable rate per kWh (Power NI, 2020c). As the study defined an opportunity for new solar panels, the ROC payments cannot be applied, essentially removing an estimated additional income of £200+ per year per household. The lack of incentive or grant being applied to the payback periods lengthened the return period, and arguably, the surplus could reduce the return period by up to 14 years. However, Reid and Wynn (2015) found the future domestic solar market in the UK for PV in 2025 is sustainable without financial incentives based on higher homeowner consumption, and the potential introduction of battery storage could change payback between 8 to 14 years depending on location. Determining solar electricity savings for households is challenging (McKenna *et al.*, 2019) with assumptions made for export/import figures. Furthermore, MCS (2019) has advised that owner daytime and evening occupancy require an appraisal to calculate accurate export estimates. Chesser *et al.* (2018) discovered that PV demand has a potential risk of increasing UK electricity prices due to ongoing infrastructure and operational costs of energy companies which are not in balance with decreased demand. However, the recent surge in energy market prices may rise further in 2022 due to market volatility (Ofgem, 2021), thus supporting the justification for self-sustaining energy generation.

4.3 Comparison of Remotely Sensed Results to Solar Websites and Modelled 3D Buildings

The three sampled buildings revealed that the web PV tools generated higher outputs compared to ArcGIS and the Revit models. The role of shadowing is important in accurately estimating solar values along roofs with websites, such as NREL, not accounting for shadowing (Nelson and Grubestic, 2020). Furthermore, Cole *et al.* (2016) explained that shadows decrease efficiency and acquiring the correct PV position is a profound undertaking with homeowners not having the capability to recognise output problems. Manual input is required on PV web sites to apply values which will degrade the overall results due to shadowing (Dean *et al.*, 2009). In the case of the sample buildings, no shading factor was applied, illustrating that the process is open to user interpretation. The Energy Saving Trust website has two issues that users need to account for: firstly, estimates are based on SAP 2012 calculations therefore inaccurate estimates of shading could adjust the yearly kWh by as much as 50%. Secondly, the SAP 2012 method is applied using a fixed latitude of 54.6° and 72m elevation for Northern Ireland calculations (BRE, 2014). Latitude and level are known factors influencing solar irradiation (Hofierka and Sári, 2002), and Dunseverick is at 55.2°, coastal with a height of approximately 47m AOD. A more

478 northerly location can expect a lower PV yield with approximate mapped variations from Belfast to Dunseverick
479 between 0 and 149 kWh/m² (MCS, 2012) meaning that northerly estimates could be overstated. The potential
480 of the models to provide accurate energy estimates, with less input from users, represents a significant strength
481 of the methodology.

482 There was strong agreement between the 3D models and both the LiDAR and DSM datasets compared to the
483 web analysis outputs with yearly solar radiation falling between -4% to 11.24%. However, the kWh productions
484 for the DSMs are more correlated with the PV websites compared to the Revit models due to calculation
485 limitations in Revit.

486 There is a high level of confidence in using the DSM, which provides cost-effective benefits and regular updates.
487 This project could be scaled to an all Northern Ireland analysis and aggregated to an online mapping system
488 similar to Jakubiec and Reinhart (2013) and NVRC (2019) who published electricity potential, emission reduction
489 and financial savings. NVRC set limitations on the minimum roof area, whereas this research set a low threshold
490 considering smaller outbuildings capable of 1.3 kWp. A regional model could incentivise policymakers to make
491 informed decisions and foster uptake for planning initiatives in relation to fuel poverty (Walker *et al.*, 2014), off-
492 grid homes in rural locations and carbon alleviation. Making such applications publicly accessible would appeal
493 to community residential groups when considering initiatives such as Peer to Peer (P2P) sharing networks which
494 provide an opportunity for domestic PV owners to become 'prosumers' (Gall and Stanley, 2019). P2P offers
495 economic potential for residents without the need for high organisational overheads for households (Johnson
496 and Mayfield, 2020). However, if the onus is on homeowners to fund energy schemes, affordability will prohibit
497 low-income homes from benefiting (Walker *et al.*, 2014) and strategic consideration is required of infrastructure
498 to ease energy poverty (Robinson *et al.*, 2019).

499 5 Conclusion

500 A UK rationalised methodology was presented for analysing and comparing remotely sensed datasets at roof
501 level for PV. The research identified the potential for an approximate 21.7MW installation at 14.7 GWh capacity
502 on all buildings. This represents 37.7% of the current small PV configurations in Northern Ireland installed over
503 the past ten years (Department for Business, Energy and Industrial Strategy, 2020). The domestic generation
504 could sustain approximately 64.35% of residential demand for the 6263 houses in this research. Furthermore,
505 a scalable framework is presented which could be applied to 'off the shelf' DSM data and utilised at a regional
506 level for published public consultation. The study modelled open-source LiDAR data which is static and

507 published through open portals and seen as 'data for the public good' (National Infrastructure Commission,
508 2017). In contrast, national mapping datasets are regularly updated, capturing critical changes in infrastructure,
509 buildings and vegetation. Temporal changes in the datasets influenced outputs, although the validation process
510 indicated a strong agreement between orthophotography produced 0.4m DSMs and 0.2m, 0.5m and 1.0m
511 LiDAR solar models. The high level of agreement between the DSM and LiDAR models means that DSMs
512 generated from orthoimagery offer significant advantages in modelling solar PV across large spatial scales.
513 While LiDAR is useful, the added costs and timescales involved in processing and collecting the data make it
514 less attractive for frequently updated solar PV maps. The workflows could be enhanced to compute a higher
515 kWp capacity for larger roof areas. Consideration could also be applied for contiguous roofs to eliminate
516 erroneous cells and a lower irradiation threshold. The research has proven successful for residential buildings
517 at 94%+ for UK configurations whilst highlighting the compatibility for low PV installation potential of smaller
518 buildings. Moreover, the reduction in PV costs and increasing effectiveness are appealing for smaller roofs as
519 higher outputs can be generated (Kouhestani *et al.*, 2018). As the research primarily focused on residential
520 buildings, there is potential for application to agricultural, industrial and commercial buildings for large scale roof
521 configurations. Web modelling is beneficial on an individual basis, although this study found the results higher
522 in comparison to modelled 3D and geospatial workflows. 3D solar modelling captures the intricate detail at roof
523 level but requires the surrounding terrain and structures for a fair and comparable analysis. While the
524 methodology is based on UK parameters, it could be modified to be suitable to other regions across the world.
525 The predicted increase in energy demands (Institution of Civil Engineers *et al.*, 2016) and policymakers'
526 obligation to address climate change (UK Government, 2020) clearly illustrates the importance and substantial
527 opportunity for PV to contribute towards a reduction in carbon burden.

528 6 References

- 529 Action Renewables. (2020). *Domestic Solar. How much am I saving on my bills?* Belfast: Action
530 Renewables. Available at: <https://actionrenewables.co.uk/services/domestic-solar> [Accessed 1st
531 May 2020].
- 532 Agugiaro, G., Nex, F., Remondino, F., De Filippi, R., Droghetti, S., and Furlanello, C. (2012). Solar
533 radiation estimation on building roofs and web-based solar cadastre. *ISPRS Annals of the*
534 *Photogrammetry, Remote Sensing and Spatial Information Sciences. 2012 XXII ISPRS Congress.*
535 Melbourne, 25th August–1st September 2012. Trento, Italy: 3D Optical Metrology unit, (1-2), pp.
536 177-182. <https://doi.org/10.5194/isprsannals-I-2-177-2012>.
- 537 Alganci, U., Besol, B., and Sertel, E. (2018). Accuracy assessment of different Digital Surface
538 Models. *Internal journals of Geo-Information*, 7(3). <https://doi.org/10.3390/ijgi7030114>.
- 539 Balta-Ozkan, N., Yildirim, J., and Connor, P, M. (2015). Regional distribution of photovoltaic
540 deployment in the UK and its determinants: A spatial econometric approach. *Energy Economics*,
541 51(1), pp. 417-429. <https://doi.org/10.1016/j.eneco.2015.08.003>.
- 542 Boz, M.B., Calvert, K., and Brownson, J.R.S. (2015). An automated model for rooftop PV systems
543 assessment in ArcGIS using LiDAR. *AIMS Energy*, 3(3), pp 401-420.
544 <https://doi.org/10.3934/energy.2015.3.401>.
- 545 Brodny, J., and Tutak, M. (2020). Analysing Similarities between the European Union Countries in
546 Terms of the Structure and Volume of Energy Production from Renewable Energy Sources.
547 *Energies*, 13(4). <https://doi.org/10.3390/en13040913>.
- 548 Brumen, M., Lukač, N., and Žalik, B. (2014). GIS Application for Solar Potential Estimation on
549 Buildings Roofs. *The Second International Conference on Building and Exploring Web Based*
550 *Environments*. Chamonix, France, 20th–24th April 2014. Maribor, Slovenia: University of Maribor,
551 Faculty of Electrical Engineering and Computer Science. Available at:

552 https://www.researchgate.net/publication/271830059_GIS_Application_for_Solar_Potential_Estimati
553 [on on Buildings Roofs](#) [Accessed 4th March 2020].

554 Buffat, R., Grassi, S., and Raubal, M. (2018). A scalable method for estimating rooftop solar
555 irradiation potential over large regions. *Applied Energy*, 216, pp. 389-401.
556 <https://doi.org/10.1016/j.apenergy.2018.02.008>.

557 Building Research Establishment. (2014). SAP 2012. *The Government's standard assessment*
558 *procedure for energy rating of dwellings*. 2nd Edition. Watford: BRE. Available at:
559 https://www.bre.co.uk/filelibrary/SAP/2012/SAP-2012_9-92.pdf [Accessed 8th February 2020].

560 Building Research Establishment. (2016). Consultation paper: CONSP:12. *SAP calculation of*
561 *electricity generated by solar PV systems*. Watford: BRE. Available at:
562 https://www.bre.co.uk/filelibrary/SAP/2016/CONSP-12---Treatment-of-solar-PV-systems---V1_0.pdf
563 [Accessed 1st March 2020].

564 Centre for Alternative Technology. (2020). *Photovoltaic (PV) solar panels*. Machynlleth, Wales:
565 Centre for Alternative Technology. Available at: [https://www.cat.org.uk/info-resources/free-](https://www.cat.org.uk/info-resources/free-information-service/energy/solar-photovoltaic/)
566 [information-service/energy/solar-photovoltaic/](#) [Accessed 16th February 2020].

567 Chesser, M., Hanly, J., Cassells, D., and Apergis, N. (2018). The positive feedback cycle in the
568 electricity market: Residential solar PV adoption, electricity demand and prices. *Energy Policy*, 122
569 pp. 36–44. <https://doi.org/10.1016/j.enpol.2018.07.032>.

570 Chow, A., Fung, A.S., and Li, S. (2014). GIS Modeling of Solar Neighborhood Potential at a Fine
571 Spatiotemporal Resolution. *Buildings* 2014, 4(1), pp. 195-206.
572 <https://doi.org/10.3390/buildings4020195>.

573 Cole, I.R., Palmer, D., Betts, T.R., and Gottschalg, R. (2016). A fast and effective approach to
574 modelling solar energy potential in complex shading environments. *Proceedings of 2016 32nd*
575 *European photovoltaic solar energy conference (EU-PVSEC)*. Munich, 20-24th June 2016.

576 Loughborough, UK: Loughborough University. pp. 1802-1807. Available at:
577 <https://hdl.handle.net/2134/24191> [Accessed 4th March 2020].

578 Dean, J., Kandt, A., Burman, K., Lisell, L., and Helm, C. (2009). Analysis of web-based solar
579 photovoltaic mapping tools. *Proceedings of the 3rd International Conference on Energy*
580 *Sustainability*. San Francisco, California, July 19th - 23rd 2009. Golden, Colorado. National
581 Renewable Energy Lab. <https://doi.org/10.1115/ES2009-90461>.

582 Department for Business, Energy and Industrial Strategy. (2019). *Solar photovoltaic (PV) cost data*.
583 London: Department for Business, Energy and Industrial Strategy. Available at:
584 <https://www.gov.uk/government/statistics/solar-pv-cost-data> [Accessed 20th April 2020].

585 Department for Business, Energy and Industrial Strategy. (2020). *Solar photovoltaics deployment*.
586 London: Department for Business, Energy and Industrial Strategy. Available at:
587 <https://www.gov.uk/government/statistics/solar-photovoltaics-deployment> [Accessed 20th April
588 2020].

589 Department for Infrastructure (Rivers). (2019). LiDAR Belfast city 2006, OpenData NI. Belfast:
590 OpenData NI. <https://www.opendatani.gov.uk/dataset/lidar-belfast-city-2006> [Accessed 23rd
591 February 2020].

592 Department for the Economy. (2020). *Northern Ireland Renewables Obligation*. Belfast: NIDirect.
593 Available at: <https://www.economy-ni.gov.uk/articles/northern-ireland-renewables-obligation>
594 [Accessed 14th April 2020].

595 Department of Agriculture Environment and Rural Affairs. (2019). *Northern Ireland carbon intensity*
596 *indicators 2019*. Belfast: NIDirect. Available at: [https://www.daera-ni.gov.uk/publications/northern-](https://www.daera-ni.gov.uk/publications/northern-ireland-carbon-intensity-indicators-2019)
597 [ireland-carbon-intensity-indicators-2019](https://www.daera-ni.gov.uk/publications/northern-ireland-carbon-intensity-indicators-2019) [Accessed 20th April 2020].

598 Energy Networks Association. (2014). *Distributed generation connection guide. A Guide for*
599 *connecting generation to the distribution network that falls Under G59/3 and is 50kW or Less 3-*
600 *Phase or 17kW or Single-Phase*. London. Energy Network Association. Available at:

601 [https://www.ukpowernetworks.co.uk/internet/asset/ab62c3e0-285b-40e6-b909-](https://www.ukpowernetworks.co.uk/internet/asset/ab62c3e0-285b-40e6-b909-389ba22ee1eK/A+guide+for+connecting+generation+to+the+distribution+network+G59-3+50kW+or+less+.pdf)

602 [389ba22ee1eK/A+guide+for+connecting+generation+to+the+distribution+network+G59-](https://www.ukpowernetworks.co.uk/internet/asset/ab62c3e0-285b-40e6-b909-389ba22ee1eK/A+guide+for+connecting+generation+to+the+distribution+network+G59-3+50kW+or+less+.pdf)

603 [3+50kW+or+less+.pdf](https://www.ukpowernetworks.co.uk/internet/asset/ab62c3e0-285b-40e6-b909-389ba22ee1eK/A+guide+for+connecting+generation+to+the+distribution+network+G59-3+50kW+or+less+.pdf) [Accessed 3rd January 2021].

604 Energy Saving Trust (2014). *Choosing a site and getting planning permission*. London: Energy

605 Saving Trust. Available at:

606 [https://energysavingtrust.org.uk/sites/default/files/Choosing%20a%20site%20and%20getting%20pla](https://energysavingtrust.org.uk/sites/default/files/Choosing%20a%20site%20and%20getting%20planning%20permission.pdf)

607 [nning%20permission.pdf](https://energysavingtrust.org.uk/sites/default/files/Choosing%20a%20site%20and%20getting%20planning%20permission.pdf) [Accessed 7th February 2020].

608 Energy Saving Trust. (2015). *Solar energy calculator sizing guide*. London: Energy Saving Trust.

609 Available at:

610 [https://www.pvfitcalculator.energysavingtrust.org.uk/Documents/150224_SolarEnergy_Calculator_S](https://www.pvfitcalculator.energysavingtrust.org.uk/Documents/150224_SolarEnergy_Calculator_Sizing_Guide_v1.pdf)

611 [izing_Guide_v1.pdf](https://www.pvfitcalculator.energysavingtrust.org.uk/Documents/150224_SolarEnergy_Calculator_Sizing_Guide_v1.pdf) [Accessed 19th March 2020].

612 Energy Saving Trust. (2020a). *Solar Panels*. London: Energy Saving Trust. Available at:

613 <https://energysavingtrust.org.uk/advice/solar-panels/> [Accessed 15th July 2020].

614 Energy Saving Trust. (2020b). *Solar energy calculator*. London: Energy Saving Trust. Available at:

615 <https://www.pvfitcalculator.energysavingtrust.org.uk/> [Accessed 15th July 2020].

616 ESRI. (2017). *Modelling solar radiation*. ArcMap 10.5. Redlands, California: ESRI. Available at:

617 [https://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/modeling-solar-](https://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/modeling-solar-radiation.htm)

618 [radiation.htm](https://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/modeling-solar-radiation.htm) [Accessed 31st May 2020].

619 European Commission PVGIS. (2019). *Photovoltaic Geographic Information System. Interactive*

620 *Tools*. Available at: https://re.jrc.ec.europa.eu/pvg_tools/en/#PVP [Accessed 16th July 2020].

621 European Commission PVGIS. (2020). *Photovoltaic Geographic Information System. PVGIS User*

622 *Manual*. Available at: <https://ec.europa.eu/jrc/en/PVGIS/docs/usermanual> [Accessed 1st August

623 2020].

624 Escribano, F.G., Marín-Quemada, J. M., and San Martín, G. E. (2013). RES and risk: Renewable
625 energy's contribution to energy security. A portfolio-based approach. *Renewable and Sustainable*
626 *Energy Reviews*, 26, pp. 549–559. <https://doi.org/10.1016/j.rser.2013.06.015>.

627 Finn, T. and McKenzie, P. (2020). *A high-resolution suitability index for solar farm location in*
628 *complex landscapes*, *Renewable Energy*, 158, pp. 520-533.
629 <https://doi.org/10.1016/j.renene.2020.05.121>.

630 Gagnon, P., Margolis, R., Melius, J., Phillips, C., and Elmore, R. (2016). *Rooftop solar photovoltaic*
631 *technical potential in the United States: A detailed assessment*. Golden, Colorado: National
632 Renewable Energy Laboratory. Available at: <https://www.nrel.gov/docs/fy16osti/65298.pdf>
633 [Accessed 18th August 2020].

634 Gall, N., and Stanley, G. eds. (2019). *Trading sunlight: prospects for peer to peer energy trading in*
635 *the UK solar industry*. Solar Trading Association: London, UK. Available at: [https://www.solar-](https://www.solar-trade.org.uk/wp-content/uploads/2019/12/STA-report-WEB.pdf)
636 [trade.org.uk/wp-content/uploads/2019/12/STA-report-WEB.pdf](https://www.solar-trade.org.uk/wp-content/uploads/2019/12/STA-report-WEB.pdf) [Accessed 14th August 2020].

637 Gehrke, S., Morin, K., Downey, M., N, Boehrer, N., and Fuchs, T. (2010). Semi-global matching: An
638 alternative to LiDAR for DSM generation? *International Archives of the Photogrammetry, Remote*
639 *Sensing and Spatial Information Sciences* – ISPRS. 38(1). Available at:
640 <https://pdfs.semanticscholar.org/5b36/5279c5ac32a3dc158b57a37f6827011b1be4.pdf> [Accessed
641 1st May 2020].

642 Gielen, D., Boshell, F., Saygin, D., Bazilian, M.D., Wagner, N., and Gorini, R. (2019). The role of
643 renewable energy in the global energy transformation. *Energy Strategy Reviews*, 24, pp. 38–50.
644 <https://doi.org/10.1016/j.esr.2019.01.006>.

645 Goodchild, M.F. (2009). Geographic information systems and science: today and tomorrow. *Annals*
646 *of GIS*, 15(1), pp. 3-9. <https://doi.org/10.1080/19475680903250715>.

647 Green Business Watch. (2014). *FIT in Northern Ireland. Northern Ireland Renewables Obligation*
648 *(NIRO) – FIT in Northern Ireland*. London: Green Business Watch. Available at:

649 <https://greenbusinesswatch.co.uk/feed-in-tariff-in-northern-ireland->
650 [niro#:~:text=2.,export%20it%20to%20the%20grid](https://greenbusinesswatch.co.uk/feed-in-tariff-in-northern-ireland-niro#:~:text=2.,export%20it%20to%20the%20grid) [Accessed 28th August 2020].

651 Green Business Watch. (2019). *Photovoltaic Solar Panels. Solar panels can give you cost savings*
652 *and earn you income*. London: Green Business Watch. Available at:
653 <https://greenbusinesswatch.co.uk/guides/solar-panels-guide#solar-costs> [Accessed 1st September
654 2020].

655 Groppi, D., de Santoli, L., Cumo, F., and Garcia, D.A. (2018). A GIS-based model to assess
656 buildings energy consumption and usable solar energy potential in urban areas. *Sustainable Cities*
657 *and Society*, 40(1), pp. 546-558. <https://doi.org/10.1016/j.scs.2018.05.005>.

658 Historic Environment Division. (2016). *Historic Environment Division LiDAR 2014 notes*. Belfast:
659 OpenData NI. Available at: [https://www.opendatani.gov.uk/dataset/historic-environment-division-](https://www.opendatani.gov.uk/dataset/historic-environment-division-lidar-2014)
660 [lidar-2014](https://www.opendatani.gov.uk/dataset/historic-environment-division-lidar-2014) [Accessed 27th February 2020].

661 Hofierka, J. and Sári, M. (2002). The solar radiation model for Open source GIS: implementation
662 and applications. *Open source GIS - GRASS users conference*. Trento, Italy, 11th–13th September
663 2002. Ispra (VA), Italy: European Commission Joint Research Centre, Institute for Environment and
664 Sustainability. Available at:
665 [http://www.ing.unitn.it/~grass/conferences/GRASS2002/proceedings/proceedings/pdfs/Hofierka_Jar](http://www.ing.unitn.it/~grass/conferences/GRASS2002/proceedings/proceedings/pdfs/Hofierka_Jaroslavl.pdf)
666 [oslavl.pdf](http://www.ing.unitn.it/~grass/conferences/GRASS2002/proceedings/proceedings/pdfs/Hofierka_Jaroslavl.pdf) [Accessed 1st September 2020].

667 Hofierka, J., and Kaňuk, J. (2009). Assessment of photovoltaic potential in urban areas using open-
668 source solar radiation tools. *Renewable energy*, 34(1), pp. 2206-2214.
669 <https://doi.org/10.1016/j.renene.2009.02.021>.

670 Hofierka, J., and Zlocha, M. (2012). A new 3-D solar radiation model for 3-D city models.
671 *Transactions in GIS*. 16(5), pp. 681-690. <https://doi.org/10.1111/j.1467-9671.2012.01337.x>.

672 Huang, J., Tian, Z., and Fan, J. (2019). A comprehensive analysis on development and transition of
673 the solar thermal market in China with more than 70% market share worldwide. *Energy*, 174, pp.
674 611–624. <https://doi.org/10.1016/j.energy.2019.02.165>.

675 Institution of Civil Engineers, Atkins, and Infrastructure Transition Research Consortium. (2016).
676 *National needs assessment*. A vision for UK infrastructure. London: ICE, Atkins, and ITRC.
677 Available at: [https://www.ice.org.uk/getattachment/news-and-insight/policy/national-needs-](https://www.ice.org.uk/getattachment/news-and-insight/policy/national-needs-assessment-a-vision-for-uk-infrastr/National-Needs-Assessment-PDF-(1).pdf.aspx#_ga=2.47982311.1543128247.1583607692-1684163932.1581950782)
678 [assessment-a-vision-for-uk-infrastr/National-Needs-Assessment-PDF-](https://www.ice.org.uk/getattachment/news-and-insight/policy/national-needs-assessment-a-vision-for-uk-infrastr/National-Needs-Assessment-PDF-(1).pdf.aspx#_ga=2.47982311.1543128247.1583607692-1684163932.1581950782)
679 [\(1\).pdf.aspx#_ga=2.47982311.1543128247.1583607692-1684163932.1581950782](https://www.ice.org.uk/getattachment/news-and-insight/policy/national-needs-assessment-a-vision-for-uk-infrastr/National-Needs-Assessment-PDF-(1).pdf.aspx#_ga=2.47982311.1543128247.1583607692-1684163932.1581950782) [Accessed 27th
680 February 2020].

681 Invest Northern Ireland. (2013). *Solar Photovoltaics*. A best practice guide for businesses in
682 Northern Ireland. Belfast: Invest NI. Available at: [https://www.elementconsultants.co.uk/wp-](https://www.elementconsultants.co.uk/wp-content/uploads/2018/02/solar-photovoltaics-a-best-practice-guide-for-businesses-in-northern-ireland1.pdf)
683 [content/uploads/2018/02/solar-photovoltaics-a-best-practice-guide-for-businesses-in-northern-](https://www.elementconsultants.co.uk/wp-content/uploads/2018/02/solar-photovoltaics-a-best-practice-guide-for-businesses-in-northern-ireland1.pdf)
684 [ireland1.pdf](https://www.elementconsultants.co.uk/wp-content/uploads/2018/02/solar-photovoltaics-a-best-practice-guide-for-businesses-in-northern-ireland1.pdf) [Accessed 8th September 2020].

685 Jacobson, M.Z., Delucchi, M.A., Bauer, Z.A., Goodman, S.C., Chapman, W.E., Cameron, M.A.,
686 Bozonnat, C., Chobadi, L., Clonts, H.A., Enevoldsen, P., and Erwin, J.R., (2017) 100% Clean and
687 Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World.
688 *Joule*, 1(1), pp. 108–121. <https://doi.org/10.1016/j.joule.2017.07.005>.

689 Jacques, D. A., Goodling, J., Giesekam, J.J., Tomlin, A.S., and Crook, R. (2014). Methodology for
690 the assessment of PV capacity over a city region using low-resolution LiDAR data and application to
691 the City of Leeds (UK). *Applied Energy*, 124, pp. 28–34.
692 <https://doi.org/10.1016/j.apenergy.2014.02.076>.

693 Jakubiec, J.A., and Reinhart, C.F. (2013). A method for predicting city-wide electricity gains from
694 photovoltaic modules based on LiDAR and GIS data combined with hourly Daysim simulations.
695 *Solar Energy*, 93, pp. 127–143. <https://doi.org/10.1016/j.solener.2013.03.022>.

696 Jochem, A., Höfle, B., Hollaus, M., and Rutzinger, M. (2009). Object detection in airborne LIDAR
697 data for improved solar radiation modeling in urban areas. In: Bretar, F., Pierrott-Deseilligny, M., and

698 Vosselman, G. eds. *Proceedings of the workshop Laser scanning 2009, International Archives of*
699 *Photogrammetry, 38 part3/W8*. Paris, France, 1st–2nd September 2009. Available at:
700 https://www.isprs.org/PROCEEDINGS/XXXVIII/3-W8/papers/1_laserscanning09.pdf [Accessed 20th
701 September 2020] .

702 Johnson, R. C., and Mayfield, M. (2020). The economic and environmental implications of post
703 feed-in tariff PV on constrained low voltage networks. *Applied Energy*, 279.
704 <https://doi.org/10.1016/j.apenergy.2020.115666>.

705 Kausika, B. B., Dolla, O., Folkerts, W., Siebenga, B., Hermans, P., and van Sark, W.G.J.H.M.
706 (2015). Bottom-up Analysis of the Solar Photovoltaic Potential for a City in the Netherlands - A
707 Working Model for Calculating the Potential using High Resolution LiDAR Data. *SMARTGREENS*
708 *2015 - 4th International Conference on Smart Cities and Green ICT Systems, Proceedings*, pp. 129-
709 135. <https://doi.org/10.5220/0005431401290135>.

710 Khan, S. B. (2017). *Web app sheds light on solar energy potential*. ESRI. California: ESRI. Available
711 at: [https://www.esri.com/about/newsroom/wp-content/uploads/2018/09/web-app-sheds-light-on-
712 solar-energy-potential.pdf](https://www.esri.com/about/newsroom/wp-content/uploads/2018/09/web-app-sheds-light-on-solar-energy-potential.pdf) [Accessed 31st May 2020].

713 Khanna, D. (2020). *Learn ArcGIS*. Estimate solar power potential. Determine how much electricity
714 could be generated from solar power in a city neighbourhood. ESRI. California: ESRI. Available at:
715 <https://learn.arcgis.com/en/projects/estimate-solar-power-potential/> [Accessed 31st January 2020].

716 Kodysh, J.B., Omitaomu, O.A., Bhaduri, B.L. and Neish, B.S. (2013). Methodology for estimating
717 solar potential on multiple building rooftops for photovoltaic systems. *Sustainable Cities and*
718 *Society*, 8 (1), pp. 31-41. Available at: <https://doi.org/10.1016/j.scs.2013.01.002>.

719 Kouhestani, F.M., Byrne, J., Johnson, D., Spencer, L., Hazendonk, P., and Brown, B. (2018).
720 Evaluating solar energy technical and economic potential on rooftops in an urban setting: the city of
721 Lethbridge, Canada. *International Journal of Energy and Environmental Engineering* (2019), 10, pp.
722 13–32. <https://doi.org/10.1007/s40095-018-0289-1>.

723 Land and Property Services. (2016a). *East Belfast_29_05_2013*. Belfast: OpenDataNI. Available at:
724 [https://www.opendatani.gov.uk/dataset/osni-open-data-river-basin-lidar-2013-dtms-and-](https://www.opendatani.gov.uk/dataset/osni-open-data-river-basin-lidar-2013-dtms-and-dsms/resource/b946bf37-e8a1-4c98-b907-f501f0a19f4b)
725 [dsms/resource/b946bf37-e8a1-4c98-b907-f501f0a19f4b](https://www.opendatani.gov.uk/dataset/osni-open-data-river-basin-lidar-2013-dtms-and-dsms/resource/b946bf37-e8a1-4c98-b907-f501f0a19f4b) [Accessed 13th April 2020].

726 Land and Property Services. (2016b). *OSNI open data largescale boundaries – NI outline*. Belfast:
727 OpenData NI. Available at: [https://www.opendatani.gov.uk/dataset/osni-open-data-50k-boundaries-](https://www.opendatani.gov.uk/dataset/osni-open-data-50k-boundaries-ni-outline)
728 [ni-outline](https://www.opendatani.gov.uk/dataset/osni-open-data-50k-boundaries-ni-outline) [Accessed 10th February 2020].

729 Land and Property Services. (2018a). *Ordnance Survey of Northern Ireland Mapping the way to*
730 *digital excellence*. OSNI Product Guide Booklet. Belfast: Land and Property Services. Available at:
731 <https://support.spatialni.gov.uk/nima/DownloadDocs/Products/OSNI-Product-Guide-booklet.pdf>
732 [Accessed 13th April 2020].

733 Land and Property Services. (2018b). *OSNI orthophotography OSNI Digital Library*. Belfast: Land
734 and Property Services. [https://mapshop.nidirect.gov.uk/Catalogue/Digital-](https://mapshop.nidirect.gov.uk/Catalogue/Digital-products/Orthophotography)
735 [products/Orthophotography](https://mapshop.nidirect.gov.uk/Catalogue/Digital-products/Orthophotography) [Accessed 13th April 2020].

736 Land and Property Services. (2018c). *OSNI DSM, OSNI Digital Library*. DSM Belfast: Land and
737 Property Services. [Accessed 25th March 2020].

738 Land and Property Services. (2019). *OSNI fusion basemap, OSNI Digital Library*. Belfast: Land and
739 Property Services. [https://mapshop.nidirect.gov.uk/Catalogue/Digital-products/OSNI-Large-Scale-](https://mapshop.nidirect.gov.uk/Catalogue/Digital-products/OSNI-Large-Scale-Mapping/OSNI-Large-scale-tiles)
740 [Mapping/OSNI-Large-scale-tiles](https://mapshop.nidirect.gov.uk/Catalogue/Digital-products/OSNI-Large-Scale-Mapping/OSNI-Large-scale-tiles) [Accessed 25th March 2020].

741 Land and Property Services. (2020a). *Workshop facilitated by Land and Property Services*
742 *photogrammetry team*: Belfast. Land and Property Services. 18th February 2020.

743 Land and Property Services. (2020b). *OSNI Open Data - 1:10,000 Raster - Mid Scale Raster*.
744 Belfast: OpenDataNI. Available at: [https://www.opendatani.gov.uk/dataset/osni-open-data-1-10000-](https://www.opendatani.gov.uk/dataset/osni-open-data-1-10000-raster-mid-scale-raster)
745 [raster-mid-scale-raster](https://www.opendatani.gov.uk/dataset/osni-open-data-1-10000-raster-mid-scale-raster) [Accessed 19th February 2020].

746 Latif, Z.A., Zaki, N, A, M., and Salleh, S, A. (2012). GIS-based Estimation of Rooftop Solar
 747 Photovoltaic Potential using LiDAR. *2012 IEEE 8th International Colloquium on Signal Processing
 748 and its Applications*, pp. 388-392, <https://doi.org/10.1109/cspa.2012.6194755>.

749 Levinson, R., Akbari, H., Pomerantz, M., and Gupta, S. (2009). Solar access of residential rooftops
 750 in four California cities. *Solar Energy*, 83(1), pp. 2120-2135.
 751 <https://doi.org/10.1016/j.solener.2009.07.016>.

752 Lingfors, D., Bright, J.M., Engerer, N.A., Ahlberg, J., Killinger, S., and Widén, J. (2017). Comparing
 753 the capability of low- and high-resolution LiDAR data with application to solar resource assessment,
 754 roof type classification and shading analysis. *Applied Energy*, 205. pp. 1216-1230.
 755 <http://dx.doi.org/10.1016/j.apenergy.2017.08.045>.

756 Liu, D., Liu, J., Wang, S., Xu, M., and Akbar, S, J. (2019). Contribution of international photovoltaic
 757 trade to global greenhouse gas emission reduction: the example of China. *Resources, Conservation
 758 and Recycling*, 143, pp. 114–118. <https://doi.org/10.1016/j.resconrec.2018.12.015>.

759 Lloyd, H. (2018). *A Distributed Energy Future for the UK*. Buckingham Street, London: Institute for
 760 Public Policy Research. Available at: [https://www.ippr.org/research/publications/a-distributed-
 761 energy-future](https://www.ippr.org/research/publications/a-distributed-energy-future) [Accessed 22nd February 2020].

762 MacIntyre, S. (2019). *The Utility of Solar Photovoltaic Panels at 55 Degrees North: Solar PV Utility
 763 in Northern Ireland*. Belfast: Ulster University. Available at:
 764 [https://pure.ulster.ac.uk/en/publications/the-utility-of-solar-photovoltaic-panels-at-55-degrees-north-
 765 sola](https://pure.ulster.ac.uk/en/publications/the-utility-of-solar-photovoltaic-panels-at-55-degrees-north-sola) [Accessed 1st May 2020].

766 Mac Kinnon, M. A., Brouwer, J., and Samuelsen, S. (2018). The role of natural gas and its
 767 infrastructure in mitigating greenhouse gas emissions, improving regional air quality, and renewable
 768 resource integration. *Progress in Energy and Combustion Science*, 64, pp. 62–92.
 769 <https://doi.org/10.1016/j.pecs.2017.10.002>.

770 Mainzer, K., Killinger, S., McKenna, R., and Fichtner, W. (2017). Assessment of rooftop photovoltaic
771 potentials at the urban level using publicly available geodata and image recognition techniques.
772 *Solar Energy*, 155(2017), pp. 561-573. <https://doi.org/10.1016/j.solener.2017.06.065>.

773 Margolis, R., Gagnon, P., Melius, J., Philip, C., and Elmore, R. (2017). Using GIS-based methods
774 and LiDAR data to estimate rooftop solar technical potential in US cities. *Environmental research*
775 *letters*, 12(7). <https://doi.org/10.1088/1748-9326/aa7225>.

776 Martín, A, M., Domínguez, J., and Amador, J. (2015). Applying LiDAR datasets and GIS based
777 model to evaluate solar potential over roofs: a review. *AIMS Energy*, 3(3), pp. 326-343.
778 <https://doi.org/10.3934/energy.2015.3.326>.

779 McKenna, E., Pless, P., and Darby, S. (2018). Solar photovoltaic self-consumption in the UK
780 residential sector: new estimates from a smart grid demonstration project. *Energy Policy*, 124(1), pp.
781 482-491. <https://doi.org/10.1016/j.enpol.2018.04.006>.

782 McKenna, E., Webborn, E., Leicester, P., and Elam, S. (2019). Analysis of international residential
783 solar PV self-consumption. *ECEEE 2019 Summer Study on energy efficiency: Is efficient sufficient?*
784 Belambra Presqu'île de Giens, France, 3rd–14th June 2019. Stockholm: European Council for an
785 Energy Efficient Economy. Available at:
786 [https://www.researchgate.net/publication/333756616_Analysis_of_international_residential_solar_P](https://www.researchgate.net/publication/333756616_Analysis_of_international_residential_solar_PV_self-consumption)
787 [V self-consumption](https://www.researchgate.net/publication/333756616_Analysis_of_international_residential_solar_PV_self-consumption) [Accessed 1st May 2020].

788 Melius, J., Margolis, R., and Ong, S. (2013). *Estimating rooftop suitability for PV: A review of*
789 *methods, patents, and validation techniques*. Golden, Colorado: National Renewable Energy
790 Laboratory. Available at: <https://www.nrel.gov/docs/fy14osti/60593.pdf> [Accessed 18th August 2020].

791 Microgeneration Certification Scheme. (2012). *Guide to the installation of photovoltaic systems*.
792 London: MCS. Available at: [https://mcscertified.com/wp-content/uploads/2019/08/PV-Book-](https://mcscertified.com/wp-content/uploads/2019/08/PV-Book-ELECTRONIC.pdf)
793 [ELECTRONIC.pdf](https://mcscertified.com/wp-content/uploads/2019/08/PV-Book-ELECTRONIC.pdf) [Accessed 1st March 2020].

794 Microgeneration Certificate Scheme. (2019). *Determining the electrical self-consumption of*
795 *domestic solar photovoltaic (PV) installations with and without electrical energy storage*. London:
796 MCS. Available at: [https://mcscertified.com/wp-content/uploads/2019/08/MGD-003-Guidance-Note-](https://mcscertified.com/wp-content/uploads/2019/08/MGD-003-Guidance-Note-Self-Consumption_.pdf)
797 [Self-Consumption_.pdf](https://mcscertified.com/wp-content/uploads/2019/08/MGD-003-Guidance-Note-Self-Consumption_.pdf) [Accessed 14th April 2020].

798 Microgeneration Certificate Scheme. (2020). *Solar Photovoltaic (PV)*. Daresbury, UK:
799 Microgeneration Certificate Scheme. Available at: <https://mcscertified.com/> [Accessed 14th April
800 2020].

801 Moudrý, V., Beková, A., and Lagner, O. (2019) Evaluation of a high resolution UAV imagery model
802 for rooftop solar irradiation estimates. *Remote Sensing Letters*, 10(11), pp.1077–1085.
803 <https://doi.org/10.1080/2150704X.2019.1649735>.

804 National Infrastructure Commission. 2017. *Data for public good*. London: National Infrastructure
805 Commission. Available at: <https://nic.org.uk/app/uploads/Data-for-the-Public-Good-NIC-Report.pdf>
806 [Accessed 25th April 2020].

807 National Renewable Energy Laboratory. (2020). *Welcome to the new PVWatts*. Golden, Colorado:
808 NREL. Available at: https://pvwatts.nrel.gov/version_6.php [Accessed 19th February 2020].

809 Nelson, J, R., and Grubestic, T, H. (2020). The use of LiDAR versus unmanned aerial systems
810 (UAS) to assess rooftop solar energy potential. *Sustainable Cities and Society*, 61.
811 <https://doi.org/10.1016/j.scs.2020.102353>.

812 Northern Ireland Authority for Utility Regulation (2019). *Utility Regulator comments on Power NI's*
813 *tariff increase*. Belfast: NIAUR. Available at: [https://www.uregni.gov.uk/news-centre/utility-regulator-](https://www.uregni.gov.uk/news-centre/utility-regulator-comments-power-nis-tariff-increase)
814 [comments-power-nis-tariff-increase](https://www.uregni.gov.uk/news-centre/utility-regulator-comments-power-nis-tariff-increase) [Accessed 8th May 2020].

815 Northern Ireland Electricity Networks. (2014). *Decision tree for distributed generated connections*.
816 Belfast: NIE Networks. Available at: [https://www.nienetworks.co.uk/documents/generation/decision-](https://www.nienetworks.co.uk/documents/generation/decision-treeev3)
817 [treeev3](https://www.nienetworks.co.uk/documents/generation/decision-treeev3) [Accessed 3rd January 2022].

818 Northern Ireland Electricity Networks. (2021). *Help and Advice. Generation connections*. Belfast:
819 NIE Networks. Available at: <https://www.nienetworks.co.uk/help-advice/faqs/generation-connections>
820 [Accessed 3rd January 2022].

821 Northern Ireland Statistics and Research Agency and Department for the Economy. (2020).
822 *Electricity consumption and renewable generation in Northern Ireland: Year ending June 2020*.
823 Belfast: Department for the Economy. Available at: [https://www.economy-](https://www.economy-ni.gov.uk/sites/default/files/publications/economy/Issue-16-Electricity-consumption-renewable-generation-northern-ireland-july-2019-june-2020.pdf)
824 [ni.gov.uk/sites/default/files/publications/economy/Issue-16-Electricity-consumption-renewable-](https://www.economy-ni.gov.uk/sites/default/files/publications/economy/Issue-16-Electricity-consumption-renewable-generation-northern-ireland-july-2019-june-2020.pdf)
825 [generation-northern-ireland-july-2019-june-2020.pdf](https://www.economy-ni.gov.uk/sites/default/files/publications/economy/Issue-16-Electricity-consumption-renewable-generation-northern-ireland-july-2019-june-2020.pdf) [Accessed 5th September 2020].

826 Northern Virginia Regional Commission. (2019). *Northern Virginia Solar Map*. Virginia: NVRC.
827 Available at:
828 <https://nvrc.maps.arcgis.com/apps/webappviewer/index.html?id=ef5c5dc969f341cc986cd431d94cdf>
829 [e9](https://nvrc.maps.arcgis.com/apps/webappviewer/index.html?id=ef5c5dc969f341cc986cd431d94cdf) [Accessed 24th January 2020].

830 Ofgem. (2020). *Microgeneration Certification Scheme (MCS): Small installations*. London: Ofgem.
831 Available at: [https://www.ofgem.gov.uk/environmental-programmes/fit/applicants/microgeneration-](https://www.ofgem.gov.uk/environmental-programmes/fit/applicants/microgeneration-certification-scheme-mcs-small-installations)
832 [certification-scheme-mcs-small-installations](https://www.ofgem.gov.uk/environmental-programmes/fit/applicants/microgeneration-certification-scheme-mcs-small-installations) [Accessed 18th August 2020].

833 Palmer, D., Cole, I., R., Betts, T., and Gottschalg, R. (2016). Assessment of potential for
834 photovoltaic roof installations by extraction of roof tilt from light detection and ranging data and
835 aggregation to census geography. *11th Photovoltaic Science, Application and Technology*
836 *Conference (PVSAT-11)*. Leeds, UK, 15th–17th April 2015. London: The Institution of Engineering
837 and Technology. *IET Renewable power generation*, 1(4), pp. 467-473. [https://doi.org/10.1049/iet-](https://doi.org/10.1049/iet-rpg.2015.0388)
838 [rpg.2015.0388](https://doi.org/10.1049/iet-rpg.2015.0388).

839 Palmer, D., Cole, I., R., Betts, T., and Gottschalg, R. (2018). Estimating rooftop capacity for PV: Are
840 we asking the right question? *Proceedings of the 14th Photovoltaic Science, Applications and*
841 *Technology Conference (PVSAT-14)*. London, 18th–19th April 2018. Oxfordshire, UK: The Solar
842 Energy Society. Available at: <https://hdl.handle.net/2134/33086> [Accessed 14th April 2020].

843 Pan, X., Yang, F., Gao, L., Chen, Z., Zhang, B., Fan, H., Ren, J. (2019) Building Extraction from
844 High-Resolution Aerial Imagery Using a Generative Adversarial Network with Spatial and Channel
845 Attention Mechanisms. *Remote Sensing*, 11. <https://doi.org/10.3390/rs11080917>

846
847 Power NI. (2020a). *Sell your electricity*. Current prices. Belfast: Power NI. Available at:
848 <https://powerni.co.uk/business/products-services/renewables/sell-electricity11/> [Accessed 7th May
849 2020].

850 Power NI. (2020b). *Unit rate prices. Standard rate*. Belfast: Power NI. Available at:
851 <https://powerni.co.uk/plan-prices/compare-our-plans/tariff-rates/> [Accessed 7th May 2020].

852 Power NI. (2020c). *Microgeneration tariff. Sell your electricity*. Belfast: Power NI. Available at:
853 <https://powerni.co.uk/products--services/renewableenergy/sell-electricity/> [Accessed 21st October
854 2020].

855 Rabiou, L., and Waziri, D.A. (2014). Digital Orthophoto Generation with Aerial Photographs. *Academic*
856 *Journal of Interdisciplinary Studies*, 3. <http://dx.doi.org/10.5901/ajis.2014.v3n7p133>

857 Reid, G., and Wynn, G. (2015). The future of solar power in the United Kingdom. *Energies*, (8) 1, pp.
858 7818-7832 Available at: <https://doi.org/doi:10.3390/en8087818>.

859 Robinson, C. Lindley, S., and Bouzarovski, S. (2019). The Spatially Varying Components of
860 Vulnerability to Energy Poverty. *Annals of the American Association of Geographers*, 4452, pp.
861 1188-1207. <https://doi.org/10.1080/24694452.2018.1562872>.

862 Song, X., Huang, Y., Zhao, C., Liu, Y., Lu, Y., Chang, Y., and Yang, J. (2018). An approach for
863 estimating solar photovoltaic potential based on rooftop retrieval from remote sensing images.
864 *Energies*. 11(11). <https://doi.org/10.3390/en11113172>.

865 Sovacool, B.K., and Martiskainen, M. (2020). Hot transformations: Governing rapid and deep
866 household heating transitions in China, Denmark, Finland and the United Kingdom. *Energy Policy*,
867 139. <https://doi.org/10.1016/j.enpol.2020.111330>.

868 Tiwari, A., Meir, I, A., and Karnieli, A. (2020). Object-based image procedures for assessing the
869 solar energy photovoltaic potential of heterogenous rooftops using airborne LiDAR and orthophoto.
870 *Remote Sensing*, 12(2). <https://doi.org/10.3390/rs12020223>.

871 UK Government. (2020). *PM launches UN climate summit in the UK*. Press Release, 4th February
872 2020. Available at: <https://www.gov.uk/government/news/pm-launches-un-climate-summit-in-the-uk>
873 [Accessed 5th February 2020].

874 Walker, R., Liddell, C., McKenzie, P., Morris, C., and Lagdon, S. (2014). Fuel poverty in Northern
875 Ireland: Humanizing the plight of vulnerable households. *Energy Research and Social Science*
876 *Elsevier*. 4, pp. 89–99. <https://doi.org/10.1016/j.erss.2014.10.001>.

877 Wong, M, S., Zhu, R., Liu, Z., Lu, L., Peng, J., Tang, Z., Lo, C, H., and Chan, W, K. (2016).
878 Estimation of Hong Kong's solar energy potential using GIS and remote sensing technologies.
879 *Renewable Energy*. 99 (2016), pp. 325-335. <https://doi.org/10.1016/j.renene.2016.07.003>.