Globally Scalable, QGIS-Integrated Workflow for Solar Photovoltaic System Segmentation and Capacity Estimation: A Case Study in Algeria

Authors:
Maximilian Kleebauer, Hichem Hafdaoui, Salim Bouchakour, Benedikt Häckner, Malte Lindenmeyer

This paper has been accepted for publication at the:
IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2025

DOI: 10.1109/IGARSS55030.2025.11242710
IEEE Xplore: `https://ieeexplore.ieee.org/document/11242710`

GLOBALLY SCALABLE, QGIS-INTEGRATED WORKFLOW FOR SOLAR PHOTOVOLTAIC SYSTEM SEGMENTATION AND CAPACITY ESTIMATION: A CASE STUDY IN ALGERIA

Maximilian Kleebauer[*1,2], *Hichem Hafdaoui*[3], *Salim Bouchakour*[3],
Benedikt Häckner[1], *Malte Lindenmeyer*[1]

Energy Meteorology and Geo Information System, Fraunhofer IEE, Kassel, Germany[1]
Department of Sustainable Electrical Energy Systems, University of Kassel, Germany[2]
Centre de Développement des Energies Renouvelables, CDER, Algiers, Algeria[3]

ABSTRACT

This study presents a deep learning-based approach for the segmentation of Solar Photovoltaic (PV) systems using a ResNet-based DeepLabV3 architecture. The method is seamlessly integrated into the open-source Geographic Information System QGIS environment through the user-friendly Deepness plugin and allows intuitive application on geospatial base maps anywhere in the world. A case study was conducted in the Piat region of Algeria, focusing on seven large PV systems within an autonomous power grid. After segmentation, a power density factor in megawatt-peak (MWp) was used to calculate the capacity of each identified PV system. The calculated capacities were compared with the official values of the operators, showing a mean relative error of 8.5 %. To further refine the capacity estimates, we introduce a locally adjusted factor of 73.5 MWp/km², which reflects the expected results for the region more precisely. The approach is globally applicable, easily transferable to different geographical contexts and accessible to users without programming knowledge, offering significant potential for renewable energy analysis. The dataset is publicly available for download [1] and can be used interactively [2].

Index Terms— solar photovoltaic systems, renewable energy, image segmentation, remote sensing application;

1. INTRODUCTION

The global transition towards renewable energy sources has increased the demand for efficient and scalable methods for analyzing and monitoring PV systems. Accurate segmentation of PV installations from remote sensing data is a critical step in enabling their rapid deployment and effective integration into energy systems, as highlighted in IRENA's 'Global Renewables Outlook: Energy Transformation 2050' [3]. Remote sensing and deep learning have emerged as powerful tools for object detection [4], regression [5], and segmentation [6] of PV systems from aerial and satellite imagery. Despite significant progress, most deep learning based models are trained on geographically limited datasets, which leads to challenges in their global applicability. In particular, regions in Northern Africa have a high potential for solar energy, but are still underrepresented in training datasets. This may affect the model's performance. To address this challenge, we present a practical workflow for detecting and analyzing PV systems from satellite imagery. This paper presents the application for the segmentation of PV systems, combining high-resolution satellite data with deep learning modeling. Figure 1 shows the five key steps of the workflow. Using QGIS and the Deepness plugin, satellite basemaps such as Google Maps can be processed directly, allowing the segmentation of PV systems without the need for programming knowledge. The segmented areas are then used to estimate installed capacity by applying a solar-specific power density factor. The segmentation model used in this study was previously developed and trained on diverse datasets, as described in [7]. This workflow enables scalable and user-friendly analysis of solar installations from remote sensing data.

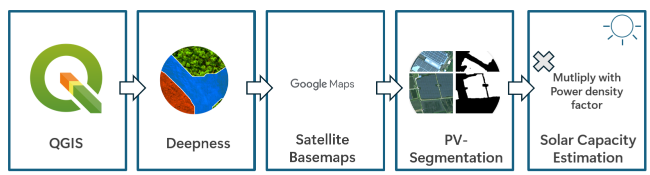

Fig. 1. Workflow for segmentation and capacity estimation of PV systems.

This study is conducted within the framework of the Development and Demonstration of a Sustainable Open Access African Union-European Union Ecosystem for Energy System Modelling (OASES) project. The project focuses on creating an integrated open-source model chain for energy system modeling, ensuring user-friendliness and accessibility for users globally. The ecosystem enables renewable energy analyses with minimal barriers and supports transparency and adoption of open-source tools for energy planning and analysis. Key components of the OASES model chain include renewable energy system detection [7], high-resolution time series generation [8], and energy system modeling integrated into platforms like the IRENA FlexTool [9, 10]. These advancements showcase the potential of open-source strategies to streamline renewable energy planning and forecasting processes, making them accessible and effective for diverse user groups.

2. STUDY AREA

Algeria, located in North Africa, is the largest country on the continent, covering an area of approximately 2.38 million square kilo-

*Corresponding author: maximilian.kleebauer@iee.fraunhofer.de

meters. The country is geographically diverse, with vast desert landscapes in the south and a Mediterranean coastline in the north. Its climate varies significantly from the dry desert regions in the south to the temperate zones in the northern coastal areas, influenced by both the Saharan climate and the Mediterranean Sea. The southern desert regions, such as the Piat (Plateau of the High Atlas) region, are characterized by hot, dry and sunny conditions with high solar radiation, making it an ideal location for solar energy projects. This region, situated in central and southern Algeria, is particularly known for its low population density, vast flat terrain, and minimal vegetation. In fact, the average solar radiation in the region is between 5 to 7 kWh/m² per day, which is among the highest in the world [11, 12].

Algeria's Piat region relies heavily on gas turbine-based power generation, which poses logistical and environmental challenges. The region's enormous solar potential, estimated at over 22,000 MWp, remains largely untapped, with a capacity of just 53 MWp in 2024. In total, there are seven systems that were installed between 2015 and 2016 [13]. Transitioning to solar energy offers a sustainable solution to reduce fuel dependence, lower costs, and improve energy security. Algeria aims to generate 27 % of its electricity from renewables by 2030, with solar as a key contributor [14, 15, 16]. Integrating hybrid systems—combining gas turbines with solar and wind power—could enhance grid reliability while reducing the carbon footprint, aligning with national climate goals [17].

3. MATERIALS AND METHODS

3.1. PV-Segmentation Model

The PV-Segmentation model was developed based on an approach that uses a DeepLabV3 ResNet101 architecture. The architecture leverages the DeepLabV3 network [18] with Atrous Spatial Pyramid Pooling (ASPP) to capture multi-scale context effectively. By integrating ResNet101 [19] as backbone, the model is well-suited for complex segmentation tasks. Various image datasets were used for training, including Unmanned Aerial Vehicles, aerial, and satellite imagery, at six different resolutions ranging from 0.1 m to 3.2 m. The training data sets were collected from different regions around the world, including France, Germany, and China, to ensure a broad representation of PV system characteristics. However, no training data from African countries was included, which could limit the model's performance in Algeria.

To achieve high segmentation accuracy and generalizability across different image sources, an extensive hyperparameter search was conducted. Details of this tuning process are described in [7], which identified the following final parameter combination as most effective. The model was trained for 100 epochs using binary cross-entropy (BCE) as the loss function, with the Adam optimizer, a learning rate of 0.0001, a batch size of 8, and a stride of 2. The ASPP segmentation head was configured with 2048 input channels and dilation rates of 12, 24, and 36. The data were split into training, validation, and testing sets with ratios of 83.3 %, 8.3 %, and 8.3 %, respectively. Model training was executed on a single NVIDIA Tesla A100-SXM4 with 40 GB memory and 512 GB CPU memory.

3.2. Deepness: Deep Neural Remote Sensing Plugin

The Deepness plugin is an open-source extension for QGIS that allows users to apply machine learning models directly to raster layers such as geospatial data or other matrix-based data [20]. It supports tasks such as object detection, regression, and segmentation, seamlessly integrating computer vision techniques into GIS workflows. With a model zoo that provides ready-to-use neural network models—including the freely available one used in this study— Deepness makes deep learning accessible to users without prior machine learning experience, adding modern deep learning based capabilities to traditional geospatial analyses. Deepness supports the use of remote sensing-based deep learning methods in the format open neural network exchange (ONNX). These models can be applied directly through the tool's graphical user interface to perform tasks such as detection or segmentation on basemaps like Google Satellite.

The following parameter settings were used for the segmentation task: *Input Channels Mapping* - Advanced settings with Band 1 assigned to red, Band 2 to green, and Band 3 to blue; *Resolution* - 80 cm/px; *Tile Size* - 1000 pixels; *Batch Size* - 1; *Tile Overlap* - 10 %; *Class Probability Threshold* - Applied based on self-validation with values between 0.3 and 0.5; *Removal of Small Segments* - Areas smaller than 20 pixels were filtered out; These settings and post-processing steps ensured accurate segmentation results while maintaining computational efficiency and minimizing noise in the output.

3.3. Google Satellite Basemap

Google Satellite provides high-resolution satellite imagery that can be used for geospatial analysis in a variety of disciplines. This dataset is accessible via Google Maps Satellite [21], this dataset offers detailed and realistic visual representations of the Earth's surface, including features such as buildings, roads, and natural landscapes. The imagery includes true-color (red-green-blue) channels, which facilitate the accurate identification and distinction of surface features. In the context of renewable energy analysis, Google Satellite imagery is instrumental for validating and correcting geodatasets, particularly for identifying and verifying PV systems. The high resolution and frequent updates of this dataset provide comprehensive coverage and support the integration of machine learning techniques for scalable and reliable geospatial data analysis. Furthermore, Google Satellite imagery can be integrated as a basemap in QGIS through the XYZ Tiles service. This allows users to overlay and analyze high-resolution imagery within the QGIS environment.

3.4. Validation and Solar Capacity Estimation

To determine the most suitable resolution, the segmentation model was initially tested on one PV system using the six trained input resolutions (ranging from 10, 20, 30, 80, 160 to 320 cm). The calculation of installed solar capacity was based on an estimated power density factor of approx. 80 MWp per kilometer² for fixed-tilt PV systems in 2016. This estimate reflects land requirements for utility-scale PV systems, as outlined in the study "Land Requirements for Utility-Scale PV: An Empirical Update on Power and Energy Density" [22]. In this study, a detailed analysis of power and energy densities in large-scale PV systems is carried out, taking into account differences in efficiency, design and space requirements. The derived power density factor allows for a straightforward conversion of segmented PV areas into their estimated capacity, offering a practical approach for renewable energy analysis. By applying this factor to the results, the installed capacity of PV systems in the Piat region is estimated.

4. RESULTS

This section presents the findings of the segmentation and capacity estimations. To determine the most suitable resolution, the model was initially tested on the PV system in Reggane using all available input resolutions, as shown in Figure 2.

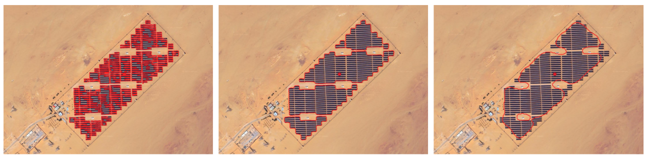

Fig. 2. Comparison of segmentation results at different resolutions for the Reggane PV system. From left to right: 20, 80, and 320 cm. The red overlay shows the results from segmentation.

A visual inspection of the segmentation results revealed that large-scale PV system boundaries are clearly identified even at coarser resolutions. With regard to the level of detail, however, significant differences can be observed in Figure 3: While the high-resolution inputs of 10 cm, 20 cm and 30 cm led to detection at panel level, the results at 80, 160 and 320 cm predominantly segmented the large-scale arrangement of PV systems.

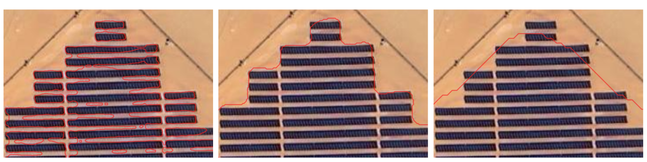

Fig. 3. Detailed comparison of segmentation results for the Reggane PV system at three selected input resolutions (20, 80, and 320 cm). The red overlays illustrate how segmentation performance varies between fine-grained panel-level detection and large-scale structure identification.

After examining various input resolutions, we chose 80 cm/px for all remaining analyses. This setting balances segmentation quality with computational efficiency, accurately capturing system boundaries while limiting runtime. Since processing time increases quadratically with resolution, 80 cm/px is especially suitable for large, ground-mounted PV parks, where it preserves key structural details without becoming prohibitively slow. Figure 4 illustrates the segmentation results for the six remaining PV systems in the Piat region, overlaid on a high-resolution satellite basemap.

The largest system, Adrar, covers 28.41 hectares, while the smallest system, Kabertene, is 3.89 hectares in size. The total area is 75.86 hectares. The distribution of system sizes indicates a dominance of medium-to-large installations in the Piat region. Table 1 summarizes the segmented areas of each PV system, the corresponding capacities estimated using a static power density of 80 MWp/km², and the official capacity values reported by operators. The table also includes the relative error, illustrating how closely the estimated capacities align with official data. Adrar emerges as the largest site, covering 28.41 ha and yielding an estimated capacity of 22.81 MWp, whereas Kabertene is the smallest at 3.89 ha

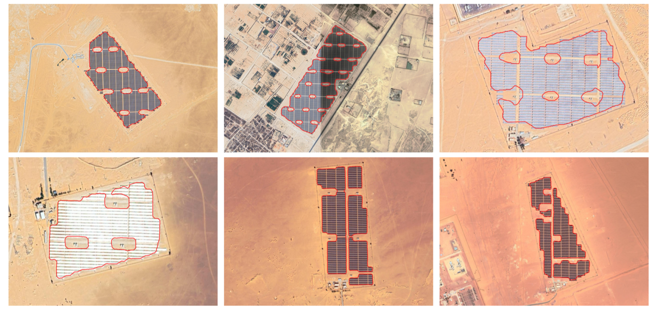

Fig. 4. Satellite imagery with segmentation results for the PV systems in the Piat region. Red outlines indicate the predicted PV areas. From left to right and top to bottom: Timimoune, Adrar, Z Kounta, Kabertene, Aoulef, and In Salah.

(3.12 MWp). Across all seven sites, the relative error ranges from 2.02 % (Reggane) up to 14.05 % (Adrar), with most errors below 10 %. When aggregated, the method estimates a total of 57.51 MWp for the entire Piat region—approximately 8.5 % higher than the official combined capacity of 53 MWp. This discrepancy underscores the need for locally refined power densities to achieve more accurate estimates.

5. DISCUSSION

The results confirm that the proposed method is capable of accurately estimating the capacities of PV systems. However, several observations show significant differences.

The resolution analysis revealed that input resolutions of 10 to and 30 cm primarily captured small-scale features at the panel level, whereas resolutions of 80 cm and above focused on the large-scale structural layout of the PV systems. This correlation is certainly highly dependent on the training sample used. The estimated total installed capacity of 57.51 MWp exceeds the official total capacity of 53 MWp by 8.5 %. This overestimation likely reflects the generic nature of the static power density factor of 80 MWp/km², derived from an average of installations in the US for 2016. Some PV systems in the Piat region were installed in 2015, when average power densities were lower due to less efficient technologies, highlighting the importance of applying year-specific power density factors.

Regional variations in factors such as land coverage, module efficiency, and site-specific design are also not fully taken into account. While the factor provides a practical baseline, local adjustments are essential to improve the accuracy of capacity estimates in regions with unique environmental conditions, such as the Piat region. The relative error varied by system size, with smaller systems like Kabertene showing lower deviations (4.00 %) and larger systems like Adrar showing higher deviations (14.05 %). This suggests that inaccuracies in segmentation and simplifications in capacity conversion have a proportionally greater impact on larger systems. Incorporating system-specific parameters such as the ground coverage ratio could further refine capacity estimates.

The lack of training data from African regions, including Algeria, may have limited the model's ability to adapt to local conditions. Increasing the geographic diversity of the training data could significantly improve the model's performance in underrepresented

PV System	Segmentation Area (ha)	Capacity Calculated (MWp)	Capacity Official (MWp)	Relative Error (%)
Z Kounta	8.13	6.53	6	8.81
Reggane	6.35	5.10	5	2.02
In Salah	6.49	5.21	5	4.19
Adrar	28.41	22.81	20	14.05
Timimoune	12.06	9.69	9	7.66
Kabertene	3.89	3.12	3	4.00
Aoulef	6.53	5.24	5	4.83

Table 1. Comparison of segmented areas (in hectares), calculated capacities using a factor of 80 MWp/km², official capacities, and relative errors in percent for the PV systems.

regions. To address the overestimation, we propose a localized correction factor of 73.5 MWp/km², which was derived by incorporating the mean relative error of 8.5 %. This adjusted factor better reflects the specific conditions of the Piat region and could reduce the discrepancies between calculated and official capacities. The application of such regional adjustments could improve the applicability of the model in other areas with similar characteristics.

In summary, the results demonstrate the robustness of the method and its potential for analyzing renewable energy at the global level. However, addressing the identified limitations is crucial to improving its accuracy and applicability in different regional contexts.

6. CONCLUSIONS

This study demonstrates a scalable and user-friendly approach for the segmentation and capacity estimation of PV systems using deep learning integrated into the QGIS environment. The proposed methodology achieves high accuracy with deviations around 8.5 %, despite the absence of local training data. Integrating the Deepness plugin ensures accessibility for non-technical users, enabling global applications. A local correction reduces the generic 80 MWp/km² power density to 73.5 MWp/km², based on the mean relative error in the Piat region. Note that "power density" here denotes installed capacity per unit area (MWp/km²), not to be confused with "capacity factor," the ratio of actual energy output to its theoretical maximum. Future work will expand regional datasets and refine area-to-capacity conversions. Overall, the approach holds strong potential for advancing renewable energy analysis and planning worldwide.

7. REFERENCES

[1] Maximilian Kleebauer, "Piat Solar Photovoltaic Systems, Algeria," Zenodo, `https://doi.org/10.5281/zenodo.15294535`, 2025, Data set.

[2] Maximilian Kleebauer, "Piat Solar Photovoltaic Systems, Algeria (Map)," Google My Maps, `https://www.google.com/maps/d/edit?mid=1mJtANHKUGB81otvNTuTCEah_QbvybtU`, 2025, Accessed: 2025-04-28.

[3] International Renewable Energy Agency (IRENA), "Global renewables outlook: Energy transformation 2050," April 2020, Accessed: 2024-12-09.

[4] Jordan M Malof, Kyle Bradbury, Leslie M Collins, and Richard G Newell, "Automatic detection of solar photovoltaic arrays in high resolution aerial imagery," *Applied energy*, vol. 183, pp. 229–240, 2016.

[5] Maximilian Kleebauer, Daniel Horst, and Christoph Reudenbach, "Semi-automatic generation of training samples for detecting renewable energy plants in high-resolution aerial images," *Remote Sensing*, vol. 13, no. 23, pp. 4793, 2021.

[6] Jiafan Yu, Zhecheng Wang, Arun Majumdar, and Ram Rajagopal, "Deepsolar: A machine learning framework to efficiently construct a solar deployment database in the united states," *Joule*, vol. 2, no. 12, pp. 2605–2617, 2018.

[7] Maximilian Kleebauer, Christopher Marz, Christoph Reudenbach, and Martin Braun, "Multi-resolution segmentation of solar photovoltaic systems using deep learning," *Remote Sensing*, vol. 15, pp. 5687, 2023.

[8] Nicolene Botha, Toshka Coleman, Gert Wessels, Maximilian Kleebauer, and Stefan Karamanski, "Power generation time series for solar energy generation: Modelling with atlite in south africa," in *Solar*. MDPI, 2025, vol. 5, p. 8.

[9] Juha Kiviluoma, Arttu Tupala, Antti Soininen, and International Renewable Energy Agency (IRENA), "Irena flextool," *Computer software*, Available online: `https://github.com/irena-flextool/flextool`, Accessed: 2024-12-02.

[10] Anni Niemi, Salim Bouchakour, Bendaas Ismail, Kada Bouchouicha, Abdelhak Razagui, Nelli Putkonen, and Juha Kiviluoma, "The curious case of wind power in the desert," *IET Conference Proceedings*, vol. 2024, pp. 536–541, 02 2025.

[11] F. Sahnoune, M. Belhamel, M. Zelmat, and R. Kerbachi, "Climate change in algeria: Vulnerability and strategy of mitigation and adaptation," *Energy Procedia*, vol. 36, pp. 1286–1294, 2013, TerraGreen 13 International Conference 2013 - Advancements in Renewable Energy and Clean Environment.

[12] Mohammed Guezgouz, Jakub Jurasz, Mohamed Chouai, Hannah Bloomfield, and Benaissa Bekkouche, "Assessment of solar and wind energy complementarity in algeria," *Energy Conversion and Management*, vol. 238, pp. 114170, 2021.

[13] Ahmed Bouraiou et al., "Status of renewable energy potential and utilization in algeria," *Journal of Cleaner Production*, vol. 246, pp. 119011, 2020.

[14] Mohamed Teggar et al., "Challenges and prospects of concentrated solar power deployment in algeria," *European Journal of Sustainable Development Research*, vol. 8, no. 4, 2024.

[15] A. Boudghene Stambouli, Z. Khiat, S. Flazi, and Y. Kitamura, "A review on the renewable energy development in algeria: Current perspective, energy scenario and sustainability issues," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 7, pp. 4445–4460, 2012.

[16] Ali Abderrazak Tadjedine et al., "Vre integrating in piat grid with afrr using pss, mppt, and pso-based techniques: A case study kabertene," *EAI Endorsed Transactions on Energy Web*, vol. 10, 2023.

[17] Mohamed Ahmedbelbachir, "Renewable energies, transition and prospects: The case of algeria," *The Eurasia Proceedings of Educational and Social Sciences*, vol. 32, pp. 62–70, Nov. 2023.

[18] Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam, "Rethinking atrous convolution for semantic image segmentation," *arXiv preprint arXiv:1706.05587*, 2017.

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[20] Przemysław Aszkowski, Bartosz Ptak, Marek Kraft, Dominik Pieczyński, and Paweł Drapikowski, "Deepness: Deep neural remote sensing plugin for qgis," *SoftwareX*, vol. 23, pp. 101495, 2023.

[21] Google, "Google satellite imagery," `https://mt1.google.com/vt/lyrs=s&x={x}&y={y}&z={z}`, 2024, Accessed: 2024-11-25.

[22] Mark Bolinger and Greta Bolinger, "Land requirements for utility-scale pv: An empirical update on power and energy density," *IEEE Journal of Photovoltaics*, vol. 12, no. 2, pp. 589–594, 2022.