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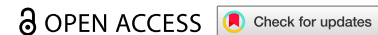


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RESEARCH ARTICLE



A google earth engine app to map ground-mounted photovoltaic system and track land use change in Italy

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ABSTRACT

Ground-mounted photovoltaic systems are expanding rapidly to meet decarbonisation targets, but their growth raises concerns about land take, farmland conversion, and biodiversity impacts. Addressing the lack of tools to monitor local land-use change across Italian municipalities, this study presents an open-access application developed on Google Earth Engine. Through an interactive interface, users can select an Italian municipality, define the year and compositing method for Sentinel-2 imagery, draw training and validation polygons, and choose among three classifiers to generate land-cover maps. The tool automatically evaluates classification accuracy, filters pixels, and converts the photovoltaic class into vector polygons. Users can then select the dataset (CORINE Land Cover + Backbone or EUCropMap) and reference year to reconstruct previous land cover and agricultural use. All results, including classified maps, photovoltaic polygons, summary tables, and charts, can be exported. Developed for Montalto di Castro (Lazio), the workflow achieved 91.05% overall accuracy and mapped 762.14 ha of installations, covering 4.02% of the entire municipal territory. Results show that most installations replaced herbaceous farmland. The workflow was successfully tested in the municipality of Guillena (Andalucía, Spain), confirming its adaptability. The application offers a practical, scalable solution for quantifying photovoltaic expansion and supporting spatial planning in Italy and across Europe.

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spatial planning

Introduction

The expansion of ground-mounted photovoltaic (PV) systems is accelerating globally as countries pursue decarbonisation and energy independence targets (Rahdan et al., 2025). According to the International Energy Agency, global renewable energy capacity is expected to increase by 2.7 times by 2030, with PV alone accounting for 80% of this growth (IEA – International Energy Agency, 2024). In the European Union, deployment is set to double, supported by the European Green Deal and the REPowerEU plan. These aim to accelerate the rollout of renewables, simplify permitting procedures, and promote spatial planning through the identification of dedicated areas (European Commission, 2019; REPowerEU, 2022). As a result of these agendas, the EU's total installed PV capacity has increased from 82 GW in 2014 to 338 GW in 2024, with nearly two-thirds of this growth occurring in the last five years alone (SolarPower Europe, 2024). This growth has been concentrated in Germany, Spain, Italy, the Netherlands, and France, which together account for 69% of all installations. Italy ranks third, with an estimated 36.2 GW of cumulative PV capacity by mid-2024 and recorded its highest annual growth in over a decade. In 2024 alone, 2.6 GW were added, representing an increase of 123% compared to 2023, largely driven by the utility-scale segment (SolarPower Europe, 2024), which typically corresponds to large PV ground-mounted

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systems (usually > 1 MW) connected to the grid, designed to deliver electricity for wholesale markets rather than self-consumption.

By the end of 2023, Italy had over 1.6 million PV installations, with around 9.2 GW of capacity installed on the ground, occupying approximately 16,400 hectares (GSE – Gestore dei Servizi Energetici, 2024). Apulia alone accounts for 4,244 hectares, followed by Sicily (1,681 ha) and Lazio (1,527 ha), which together represent 45.5% of the national ground-mounted PV area. Satellite-based estimates suggest slightly higher land use of 17,907 hectares, reflecting differences between administrative records and remote sensing methods (SNPA – Sistema Nazionale per la Protezione dell’Ambiente, 2024). These differences highlight the complementary nature of the two approaches: administrative data capture officially registered capacity but may lag behind actual deployment, while satellite observations provide spatially explicit, near-real-time snapshots that can include informal or recently installed systems not yet recorded in national databases.

At the same time, although European strategies ask Member States to identify suitable land and sea areas for renewable energy projects, while avoiding, as much as possible, environmentally valuable areas and prioritising degraded land not usable for agriculture to enable low-impact deployment (REPowerEU, 2022), ground-mounted PV remains the main driver of capacity growth, with large installations playing a growing role (IEA – International Energy Agency, 2024). In this context, the ongoing simplification of permitting procedures has raised concerns about uncontrolled land consumption, biodiversity loss, and the progressive loss of agricultural areas (Delfanti et al., 2016; Hernandez et al., 2014; Manufò, 2022).

In response, there has been growing interest in developing different methodologies to support informed spatial planning and impact assessment. For instance, in Italy, a Geographic Information System (GIS) based model was developed to estimate photovoltaic energy potential and assess trade-offs with food production, incorporating legal, technical, and economic constraints (Sacchelli et al., 2016). More recently, a multicriteria framework has been applied at the national scale to identify areas eligible for agrivoltaics, integrating solar irradiance, crop types, and environmental designations (Fattoruso et al., 2024). From a monitoring perspective, a U.S.-based study combined Sentinel-2 and Landsat time series (1983–2020) to map PV installations and estimate their construction years using object-based segmentation, supervised classification, and manual validation (Tao et al., 2023). At the regional level, a spatial optimisation framework has been used to prioritise PV development while minimising conflicts with biodiversity and agriculture through alternative allocation scenarios (Hermoso et al., 2023).

While each of these contributions enhances the spatial understanding of PV deployment, they also reflect relevant limitations. Some approaches are focused on ex-ante land suitability assessments and rely on extensive local input data, including economic values, detailed crop maps, or expert-defined weights, often without accounting for the presence of existing PV installations (Fattoruso et al., 2024; Sacchelli et al., 2016). While effective for temporal reconstruction, this workflow (Tao et al., 2023) relies on object-based segmentation and the COLD (COntinuous monitoring of Land Disturbance) algorithm, which detects land cover changes by analysing spectral trajectories across the full 38-year Landsat archive. This approach requires significant technical expertise and computational resources. Moreover, since it relies on object segmentation, it cannot distinguish between rooftop-mounted and ground-mounted PV installations. These tools are not designed to be directly used by non-specialist stakeholders, such as municipal staff or local planners, and remain confined to academic or pilot-scale applications (Hermoso et al., 2023; Sacchelli et al., 2016; Tao et al., 2023).

In this context, in response to the European Union (EU) request to identify suitable areas for PV deployment, Italian legislation has introduced specific national criteria through Ministerial Decree No. 320 of 21 June 2024, which dictates the identification of surfaces and areas suitable for the installation of renewable energy plants (MASE – Ministero dell’Ambiente e della Sicurezza Energetica, 2024). The decree also promotes the use of the digital platform “Piattaforma Aree Idonee”, developed and managed by Gestore dei Servizi Energetici S.p.A., the Italian public body responsible for promoting and supporting renewable energy development nationwide. The platform was formally established with the aim of providing adequate support to regions and provinces in the process of identifying suitable areas (MASE – Ministero dell’Ambiente e della Sicurezza Energetica, 2024). The platform functions as a web-based GIS that overlays spatial datasets on environmental constraints, protected areas, cultural heritage sites, and land use designations, allowing regional and provincial authorities to delineate areas suitable for renewable energy installations according to the criteria established in the decree. However, the platform primarily

provides screening support based on exclusionary criteria and does not offer operational tools for mapping existing PV installations, assessing land-use change, or monitoring cumulative impacts at municipal scale. Local authorities are expected to account for technical, environmental, and cultural constraints, as outlined in Article 7 of the decree. In early 2025, the Regional Administrative Court of Lazio reviewed multiple appeals from energy operators, raising concerns about the lack of consistency and objective criteria in regional planning. The Council of State had already suspended parts of the decree, highlighting the need for clearer operational guidance (FREE – Fonti Rinnovabili Efficienza Energetica, 2024; Il Sole 24 Ore, 2025).

We argue that regions and provinces lack the capacity to map, assess, and monitor these dimensions effectively at the local scale. Given that the impacts of ground-mounted PV are diverse and highly context-dependent (Liu et al., 2020; Vaverková et al., 2022; Wu et al., 2025), we believe that analyses should be conducted locally and then scaled up to map and assess broader patterns. Recent studies have shown that Google Earth Engine (GEE) can support scalable land-cover mapping and operational earth observation services, including in geomorphologically complex settings (Orusa et al., 2023a) and in workflows designed for public-administration needs (Orusa et al., 2024). However, dedicated tools that operationally map ground-mounted PV at municipal scale and link current PV footprints to pre-installation land cover, using accessible interfaces and reproducible processing chains, remain limited.

This study addresses that operational gap through three complementary pillars: evidence, empowerment, and reconstruction. First, it provides evidence by deriving reproducible, spatially explicit maps of ground-mounted PV and by quantifying the pre-existing land cover within detected PV footprints. Second, it promotes empowerment by implementing the workflow in GEE (Gorelick et al., 2017), used here as a virtual laboratory that lowers technical and computational barriers and helps bridge the digital divide between national agencies and local-level users. Third, it supports reconstruction by enabling a land-use forensic audit, linking today's PV footprints to prior land cover and thereby informing local planning, screening, and monitoring.

Building on these pillars, this study presents a flexible and user-friendly graphical interface developed in GEE. The tool enables the detection of ground-mounted PV installations and the evaluation of historical land use change across Italian municipalities.

By providing accessible, spatially explicit data, it supports a wide range of stakeholders, including local governments, planners, researchers, and community groups, in identifying development patterns, flagging potential land use conflicts, and reconstructing past transformations. In doing so, it contributes to bridging the disconnect between top-down policy directives and bottom-up spatial evidence, fostering more informed and context-sensitive energy and land use planning.

The tool was developed for the case study of Montalto di Castro (Lazio, Italy), one of the most PV-intensive municipalities in the country (GSE – Gestore dei Servizi Energetici, 2024). It was used to detect ground-mounted PV installations through supervised classification of Sentinel-2 composites, extract PV polygons, and analyse the previous land cover of these areas using CORINE Land Cover (CLC) + Backbone and EUCropMap datasets.

Moreover, to assess its transferability and scalability, the same workflow was applied to the municipality of Guillena (Seville, Spain), integrating the municipal boundaries from the Centro Nacional de Información Geográfica (CNIG – Centro Nacional de Información Geográfica, 2025). The test also demonstrated how national boundary layers can be replaced with the Eurostat GISCO dataset of European Local Administrative Units, confirming the tool's adaptability to different administrative frameworks and its potential for broader use across Europe (Eurostat–GISCO, 2024).

The full application, source code, and supplementary documentation are openly available on Zenodo (Cotti Piccinelli, 2025a), ensuring transparency, scalability, and operational flexibility.

Method

Platform and processing environment

This application was developed using GEE, a cloud-based platform tailored for the processing and analysis of large-scale geospatial data. GEE combines a massive catalogue of analysis-ready satellite imagery and

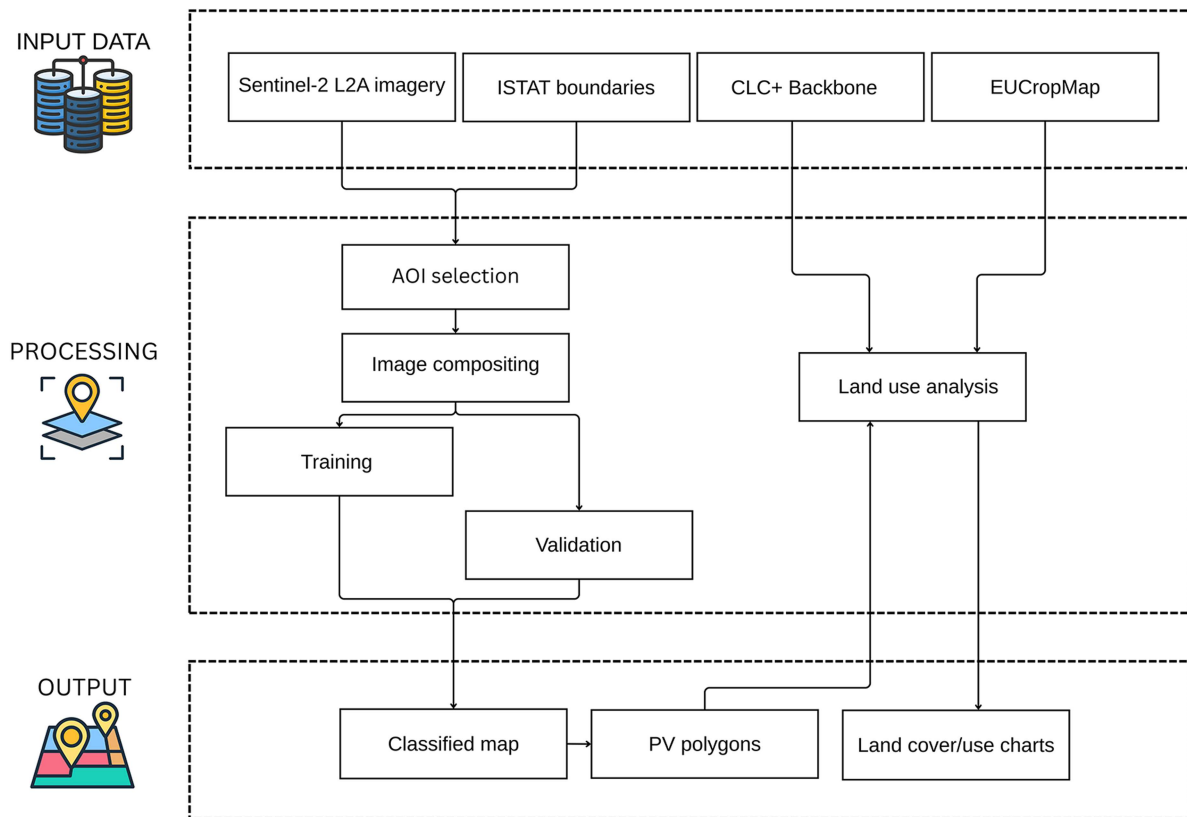


Figure 1. A flowchart illustrates a three stage data processing workflow from input data to output products, with multiple steps.

environmental datasets with a parallel computing environment accessible via a web-based application programming interface (API) and code editor (Gorelick et al., 2017). This setup enables users to run complex, data-intensive analyses directly in the cloud, without relying on local infrastructure. The tool presented here was implemented as a GUI-based App using the GEE JavaScript API, enabling interactive analysis and result visualisation through a user-friendly interface, with no need for programming knowledge. Figure 1 offers a flow chart showing the methodological steps of the study.

Input datasets

Sentinel-2 level-2A imagery

Sentinel-2 is a multispectral optical mission developed within the European Copernicus programme, designed to support land monitoring through high-resolution imagery in 13 spectral bands (Drusch et al., 2012). Sentinel-2 data have proven particularly effective for land cover mapping and land use classification due to their high spatial, spectral, and temporal resolution (Phiri et al., 2020). In this application, we use Sentinel-2 Level-2A products, which provide surface reflectance data corrected for atmospheric effects (ESA – European Space Agency, 2021).

We used the 10 m visible–NIR bands (blue B2: 490 nm, green B3: 560 nm, red B4: 665 nm, NIR B8: 842 nm) together with the 20 m SWIR bands (B11: 1610 nm; B12: 2190 nm). From these predictors, we derived three widely adopted spectral indices, the Normalised Difference Vegetation Index (NDVI; Tucker, 1979), the Normalised Difference Water Index (NDWI; McFeeters, 1996) and the Normalised Difference Built-up Index (NDBI; Zha et al., 2003), to enhance spectral separability between vegetated, water/moist and impervious or built-up surfaces. The integration of SWIR information and built-up indices is commonly used in land cover classification workflows to reduce confusion between dark artificial materials and non-vegetated surfaces. Images were filtered to retain only scenes with <5% cloud cover, and residual

clouds and shadows were masked using the Sentinel-2 Scene Classification Layer (SCL). All predictors were sampled and classified at 10 m spatial resolution; therefore, the 20 m SWIR bands were internally resampled within GEE to match the working scale.

Administrative boundaries

The selection of the Area of Interest (AOI) relies on official administrative boundaries at municipal level. For the Italian case study, the 2025 municipal boundaries released by the Italian National Institute of Statistics (ISTAT – Istituto Nazionale di Statistica, 2025) were used. However, the tool is designed to accept alternative administrative datasets, enabling its application across different countries and administrative frameworks. Users must download the corresponding shapefile (e.g. ISTAT for Italy, CNIG for Spain, or Eurostat LAU for pan-European applications), upload it to their own GEE assets as a FeatureCollection, and specify the Asset ID within the script. This modular design supports cross-country applicability as demonstrated in [Cross-country applicability](#) where the workflow is applied to Spain using CNIG municipal boundaries and further tested with the Eurostat Local Administrative Units (LAU) dataset. Detailed instructions for uploading and integrating alternative boundary datasets are included within the open-access script and user manual available on Zenodo (Cotti Piccinelli, 2025a).

CLC + backbone

The CLC + Backbone dataset is a pan-European land cover classification developed by the Copernicus Land Monitoring Service. The product is generated through a semi-automated classification workflow combining multi-temporal Sentinel-2 imagery (2017–2018 for the 2018 edition; 2020–2021 for the 2021 edition) with auxiliary datasets including digital elevation models, existing land cover products, and Very High Resolution imagery for validation (EEA – European Environment Agency, 2023, 2024). It provides wall-to-wall raster coverage at 10 m spatial resolution and is available for multiple reference years. In this application, the 2018 and 2021 layers are employed, as these represented the most recently available editions at the time of tool development. Each pixel is assigned to the dominant land cover type based on a minimum mapping unit of 0.5 ha for areal phenomena, ensuring consistency with the EAGLE (EIONET Action Group on Land monitoring in Europe) ontology (EEA – European Environment Agency, 2023, 2024). The EAGLE framework promotes standardised, hierarchical land cover concepts across Europe, ensuring semantic interoperability and enabling cross-dataset integration.

The nomenclature includes 11 core land cover classes: sealed surfaces; woody—needle-leaved trees; woody—broadleaved deciduous trees; woody—broadleaved evergreen trees; low-growing woody vegetation (bushes, shrubs); permanent herbaceous vegetation; periodically herbaceous vegetation; lichens and mosses; non- and sparsely vegetated areas; water bodies; and snow and ice.

In this application, CLC + Backbone is used to determine land cover conditions prior to PV deployment, enabling temporal comparisons and land use change assessments at municipal scale.

EUCropMap

EUCropMap is a pan-European, crop-specific land cover dataset developed by the Joint Research Centre (JRC) of the European Commission (d’Andrimont et al., 2021; Ghassemi et al., 2022). It provides high-resolution (10 m) raster data identifying the dominant crop type or pasture class. The product is available for multiple reference years (2018 and 2022) and supports detailed monitoring of agricultural land use across EU countries.

The nomenclature includes major categories of arable crops, permanent crops, and managed grasslands. Each pixel is classified into one of the following 22 land cover types: common wheat; durum wheat; barley; maize; rice; other cereals; potatoes; sugar beet; oilseed rape; sunflower; grain legumes; other root crops; other industrial crops; fodder crops; vegetables and flowers; other crops; vineyards; orchards; olive groves; pastures; fallow land; and non-agricultural land.

In this study, EUCropMap is used to characterise the previous agricultural use of areas converted to PV installations. Compared to general purpose land cover datasets, EUCropMap offers greater thematic detail for cropland differentiation, making it particularly suitable for land use change assessments in agricultural regions.

App structure and workflow

The app adopts a structure guiding users through a six-step workflow:

1. Selection of AOI

Users can select the AOI from ISTAT administrative boundaries at municipal level (Figure 2).

2. Image selection and compositing

Users select the target year (between 2018 and 2025), month, and an image aggregation method: mean, median, minimum, or maximum. Sentinel-2 Level-2A imagery is first filtered to retain scenes with less than 5% cloud cover. The selected aggregation function is then applied to generate a monthly composite, which is clipped to the AOI as shown in Figure 3. Different compositing methods are available to ensure adaptability to local landscape characteristics and seasonal variability (Schüpbach et al., 2016). Image compositing is a standard practice in remote sensing to generate cloud-free and temporally consistent inputs for classification, helping to reduce atmospheric noise and stabilise spectral signals over time (Bey et al., 2020; Holben, 1986; Sellami & Rhinane, 2023).

3. Training and validation input

The supervised classification relies on five predefined land cover classes, designed to balance PV detection accuracy, spectral separability, and ease of use for non-specialist stakeholders:

- Photovoltaic (class 0): ground-mounted PV installations.
- Agricultural (class 1): includes managed croplands, orchards, and all cultivated areas used for crop production.
- Woody vegetation (class 2): tree cover, shrubs, and forested areas.

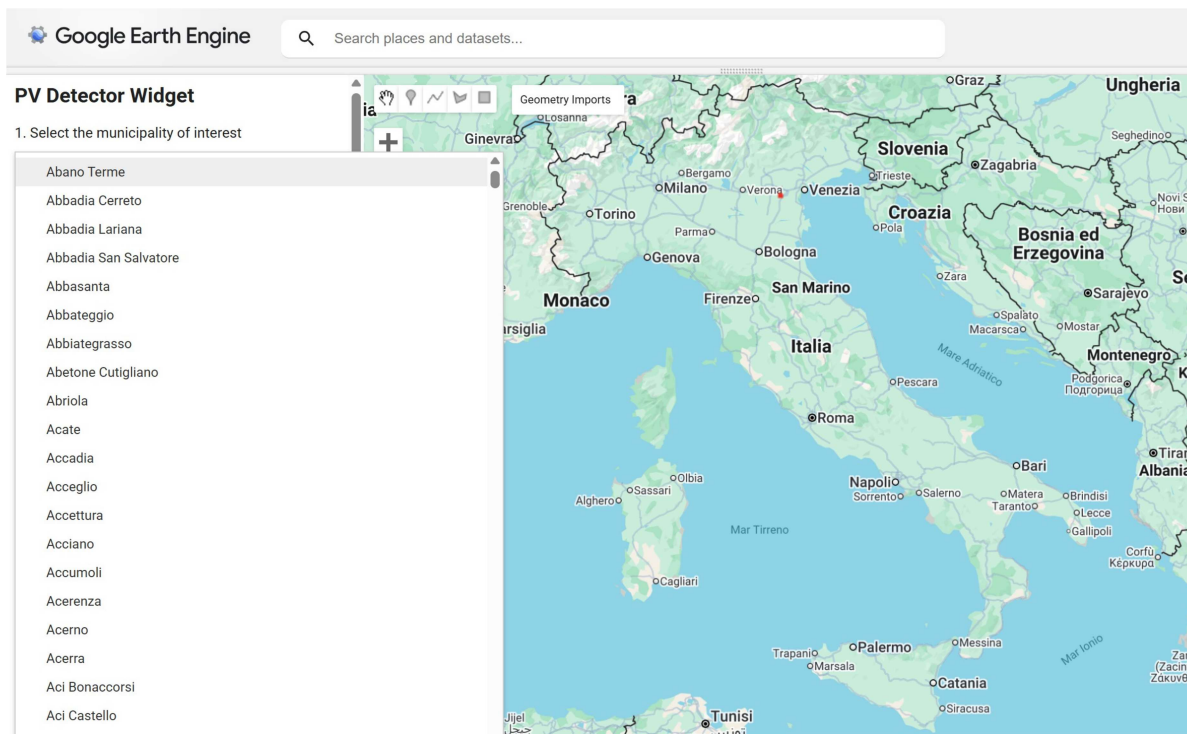


Figure 2. A screenshot shows a GEE interface with a map of Italy and a municipality selection widget.

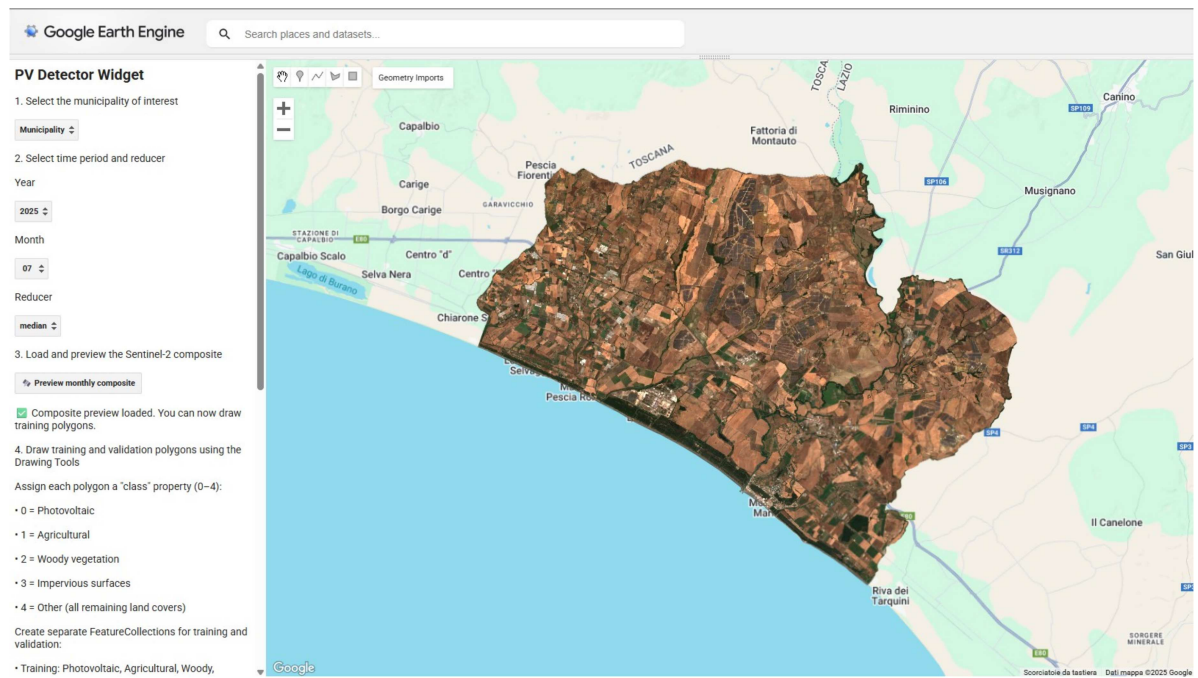


Figure 3. Screenshot of the GEE PV detector widget: example of a monthly Sentinel-2 Level-2A composite clipped to the AOI.

- Impervious surfaces (class 3): built-up areas, paved roads, buildings.
- Other (class 4): all remaining surface types not included in the categories above (e.g. water, bare soil, isolated houses).

Users must manually digitise polygons representative of each land cover class using the drawing tools provided in the GEE Code Editor. Each polygon must be assigned a numeric class property corresponding to the correct land cover code. Training and validation data must be provided as distinct FeatureCollections, one per class. The application expects the following naming convention:

- for training, use: Photovoltaic, Agricultural, Woody, Impervious, Others
- for validation, use the same names with the suffix `_val`: e.g. Photovoltaic_val, Agricultural_val, etc.

All FeatureCollections must be imported into the script interface and contain only features of the assigned class (Figure 4). The geometries used for training and validation must be spatially independent to ensure unbiased accuracy metrics. A minimum of 10 training polygons and 8 validation polygons per class is recommended, although larger samples are encouraged in heterogeneous areas. Training and validation polygons should also be geographically dispersed across the entire study area in order to capture intra-class spectral variability (e.g. differences in crop types, soil background, vegetation condition, or illumination effects). Concentrating samples in a single portion of the municipality may bias classifier performance and reduce transferability. This structured input is necessary for the application to correctly merge, process, and classify image data using the selected classifier within the GEE environment. Once these steps are completed, users can tick the box “I have finished drawing and importing polygons using ‘Import as a FeatureCollection’ with the property ‘class’” to proceed with the classification.

4. Supervised classification and accuracy assessment

The application supports three supervised classifiers: Random Forest (Breiman, 2001), Classification and Regression Trees (Breiman et al., 1984), and Minimum Distance (Wacker & Landgrebe, 1972). Users



Figure 4. A three panel diagram shows a GEE interface: (a) activation of the drawing tools within the GEE Code Editor to enable polygon digitisation. (b) example of manually drawn polygons. (c) configuration panel where each polygon is assigned a 'class' property and imported as a FeatureCollection following the required naming convention.

can select one classifier at a time from a dropdown menu. These classifiers were selected to provide users with options that differ in computational complexity, sensitivity to training sample size, and performance across heterogeneous landscapes. Offering multiple classifiers allows users to iteratively test and compare performance, selecting the algorithm that achieves the highest accuracy for their specific study area and image configuration. The classification is pixel-based and is performed on a monthly Sentinel 2 composite using training polygons provided by the user. The resulting classified image is evaluated using a confusion matrix and overall accuracy, based on the separate validation dataset, as shown in Figure 5. This step is essential to quantify the reliability of the classification and guide the selection of the optimal configuration. The use of confusion matrices and standard accuracy metrics remains the most established and recommended approach for assessing classification performance in earth observation applications (Nicolau et al., 2023). Alongside the classified map, the interface displays a colour-coded legend showing all land cover classes. It also provides summary statistics including the total area (in hectares) of the PV class, the area of the selected municipality, and the percentage of the municipal territory occupied by PV installations.

It is important to note that the application reports two PV area estimates in the console: the raw, pixel-based area derived directly from the classified raster, and a cleaned area obtained after spatial filtering. The on-map statistics panel reports only the cleaned estimate, ensuring consistency with the extracted PV polygons used for vector outputs and subsequent analyses. In fact, to reduce noise and exclude spurious detections, the application applies a combination of connected component analysis and pixel-count filtering: only contiguous clusters larger than 50 pixels are retained, which corresponds to a minimum mapping unit (MMU) of 0.50 ha at 10 m resolution ($50 \times 100 \text{ m}^2$). This step helps eliminate isolated misclassifications and ensures spatial coherence in the extracted features. Moreover, it reduces the likelihood of including rooftop PV systems, which are typically smaller than 0.5 ha even in large industrial settings (Gagnon et al., 2016).

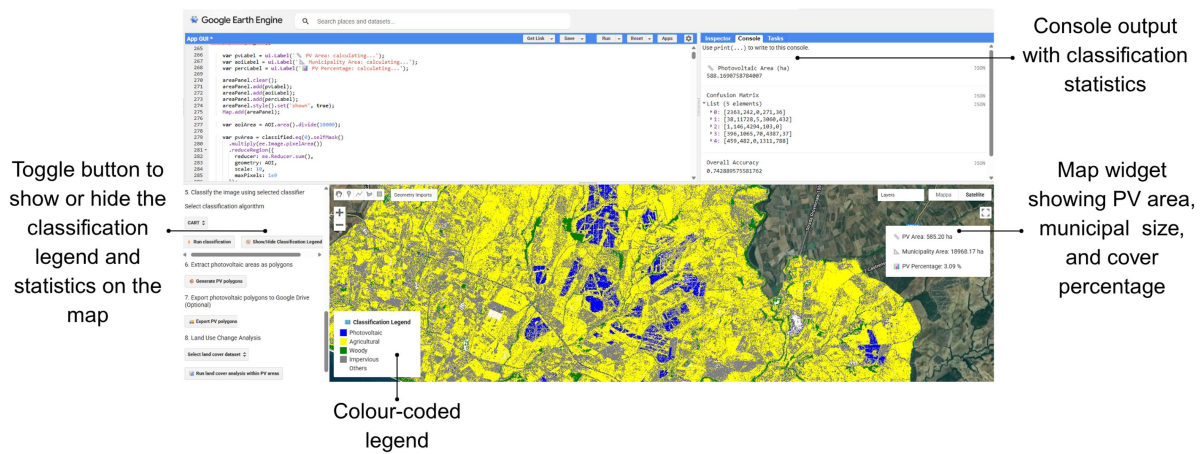


Figure 5. A screenshot display an example of land cover classification using the CART algorithm within the GEE interface. The classified map includes a colour-coded legend, while the console displays the confusion matrix, overall accuracy, and raw photovoltaic area derived from the classification. The map widget provides cleaned summary statistics after spatial filtering, including PV area, municipality size, and coverage percentage. For improved visualisation of subsequent outputs, both the legend and the statistics panel can be toggled on or off using the “Show/Hide Classification Legend” button.

As a consequence, very small or fragmented ground-mounted installations below this threshold may not be captured; however, this filtering choice is consistent with the focus on utility-scale PV farms, which are typically defined as installations larger than 1 MW (SolarPower Europe, 2024), and generally occupy around 1–2 ha per MW of installed capacity (Bolinger & Bolinger, 2022). To support this choice empirically, we performed an object-based sensitivity test of the MMU (0.10, 0.25 and 0.50 ha) on the main case study. The results (Table S1) show that reducing the MMU below 0.50 ha increases the number of mapped PV polygons but changes the total mapped PV area only marginally, indicating that the 0.50 ha threshold primarily removes small, fragmented objects while preserving the overall PV extent for the intended purpose of the tool. It is recommended that users test different combinations of classifiers (e.g. CART), compositing methods (e.g. median), and seasonal periods (e.g. July), selecting the configuration with the highest accuracy before proceeding to polygon extraction and land cover change analysis. To speed up the workflow, a temporary block can be added in the script to keep the AOI selection fixed on the chosen municipality. This optional step, intended to facilitate iterative testing and accuracy comparison, is explained in detail in the user manual available on Zenodo (Cotti Piccinelli et al., 2025a).

5. Photovoltaic polygon extraction

The classified raster is filtered to isolate the photovoltaic class. The resulting binary mask is then vectorised to convert the clean raster output into polygon geometries representing ground-mounted PV areas. The extracted PV polygons are visualised on the map and made available for export, allowing users to conduct further or external spatial analysis as shown in Figure 6. GEE enables multiple export formats, including CSV, GeoJSON, KML, KMZ, SHP, and TFRRecord, enabling direct integration with most GIS and data analysis platforms.

6. Land cover change analysis

Extracted PV polygons can be overlaid with either CLC Backbone (2018, 2021) or EUCropMap (2018, 2022), as selected by the user, to determine previous land use (Figure 7). The app computes both absolute (hectares) and percentage area conversions, showing which land cover types have been replaced by PV. Results are visualised with pie and bar charts, and all outputs (charts, tables) are downloadable. Also, results are summarised and displayed in console. Classification and land use change maps can also be exported for further spatial analysis.

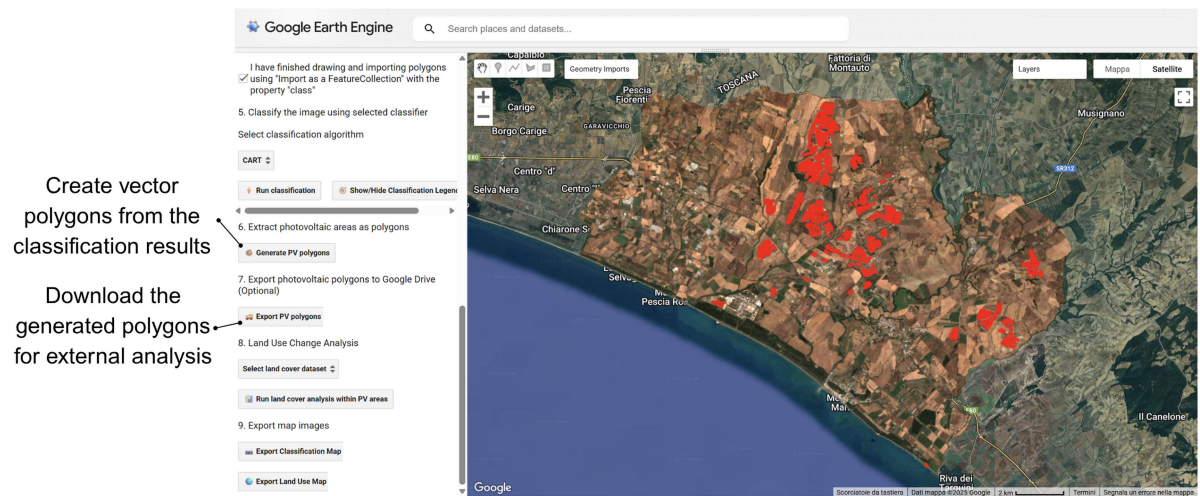


Figure 6. A screenshot shows extracted PV polygons visualised in red on map. These geometries are derived by vectorising the classified raster after isolating the PV class and applying spatial filtering.

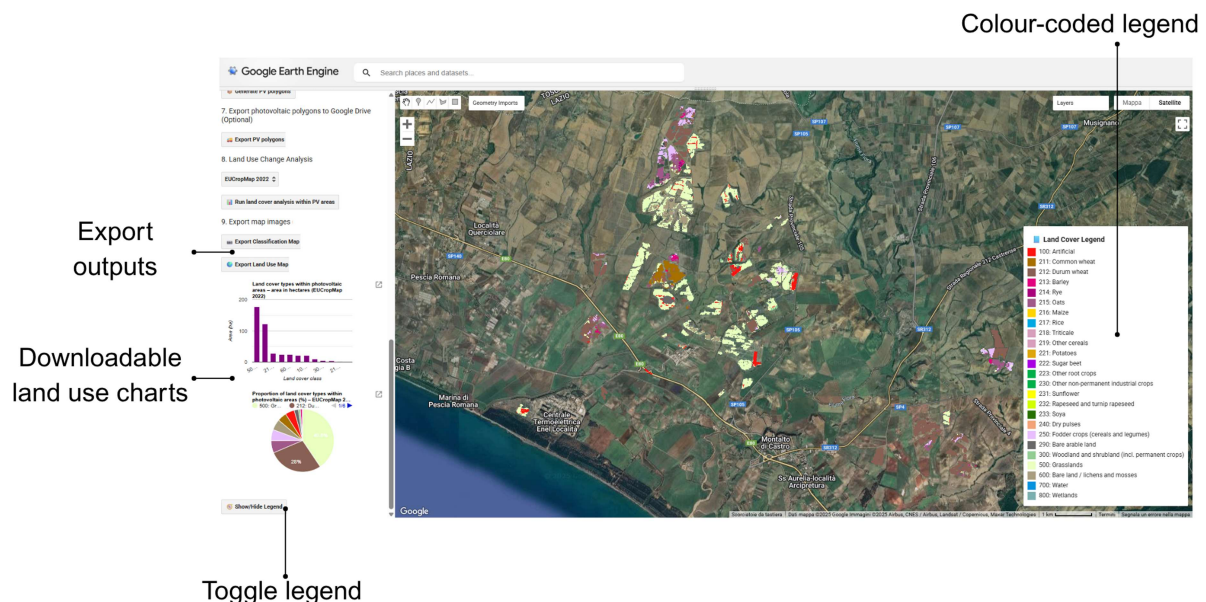


Figure 7. Example of land use analysis based on EUCropMap 2022. Extracted PV polygons are intersected with the crop type map to identify previous land cover. The interface displays a detailed legend, a bar chart showing the area (in hectares) occupied by each crop type within PV areas, and a corresponding pie chart representing percentage values.

Results: tool application and transferability assessment

Context and relevance of the Montalto di Castro case study

The tool was tested in the municipality of Montalto di Castro, located in the province of Viterbo (Lazio, Central Italy), selected as a representative case study. According to national energy statistics, the province of Viterbo hosts one of the largest concentrations of installed PV capacity in central Italy, reflecting its strategic role in utility-scale PV deployment (GSE – Gestore dei Servizi Energetici, 2024).

In particular, Montalto di Castro offers favourable environmental and infrastructural conditions, such as flat terrain, high solar irradiance, and a consolidated electricity grid. In fact, the area was initially intended for a nuclear power plant, never activated, and was later converted into a major thermoelectric site, which further reinforced its suitability for large-scale PV development (ANSA, 2022).

In recent years, the municipality has become a focal point in the national debate on renewable energy (Il Messaggero, 2023; ViterboToday, 2023). Multiple PV installations have raised concerns among local authorities and citizens about land saturation, agricultural land loss, and a lack of spatial coordination. In 2023, the municipal council held a special session to request national intervention (Il Messaggero, 2023), and local committees have publicly denounced what they describe as uncontrolled PV expansion (ViterboToday, 2023).

Given this combination of technical, strategic, and socio-political relevance, Montalto di Castro represents a typical context of intensive PV development in Italy characterised by a rapid proliferation of utility-scale projects in agriculturally productive areas. It was therefore selected as a representative case to develop and calibrate the tool, before assessing its transferability to other European contexts.

Classification results from tool application

The tool was applied to the municipality of Montalto di Castro using Sentinel-2 imagery acquired in July 2025, with a median composite and the Random Forest classifier.

The classification achieved an overall accuracy of 91.05%, as estimated by the confusion matrix derived from the validation dataset (Table 1). The confusion matrix indicates high overall performance and good class separability, especially for agricultural (class 1) and woody vegetation (class 2), which are largely concentrated on the main diagonal. The photovoltaic class (class 0) is also well detected, with very limited misclassification, occurring almost exclusively towards impervious surfaces (class 3), consistent with partial spectral similarity between PV panels and artificial materials.

Most residual uncertainty involves impervious (class 3) and other (class 4). Impervious is mainly confused with agricultural and other, while other is frequently misclassified as impervious. This pattern likely reflects the heterogeneous and transitional nature of these classes (e.g. mixed artificial surfaces, bare soil, rural infrastructure), which increases spectral overlap. Overall, the results support reliable PV mapping, with remaining errors concentrated in the discrimination of mixed/artificial surface types.

Following the classification, a total of 762.14 hectares were identified as ground-mounted PV areas within the municipal boundaries. Considering the total municipal surface of 18,968.17 hectares, this corresponds to approximately 4.02% of the territory being occupied by PV installations (Figure 8).

To evaluate robustness with respect to key classifier settings and alternative algorithms, a sensitivity analysis was performed (Supplementary Table S2). Random Forest performance remained stable across runs with 10, 100 and 300 trees, with overall accuracy ranging from 91.05% to 91.35% (marginal gain <0.3%). Runs with 500 trees could not be completed in GEE due to memory limitations. In light of this, the operational configuration with 10 trees was retained as a computationally efficient yet robust solution for the tool, balancing classification performance. CART and Minimum Distance yielded lower overall accuracy.

Land use analysis

To investigate previous land use within detected PV areas, we performed a spatial overlay between the extracted PV polygons and both CLC + Backbone and EUCropMap. These two datasets provide complementary information at different levels of thematic detail: CLC + Backbone offers broad land cover categories suitable for characterising general land cover transitions, while EUCropMap provides crop-specific classifications that enable fine-scale analysis of agricultural land use change. Using both datasets

Table 1. Confusion matrix for the municipality of Montalto di Castro. Rows represent actual classes; columns represent predicted classes.

Actual	Predicted				
	Photovoltaic (0)	Agricultural (1)	Woody (2)	Impervious (3)	Others (4)
Photovoltaic (0)	1923	0	0	17	0
Agricultural (1)	2	19331	29	248	120
Woody (2)	0	3	3699	53	0
Impervious (3)	14	1055	22	8121	1148
Other (4)	0	28	0	385	930

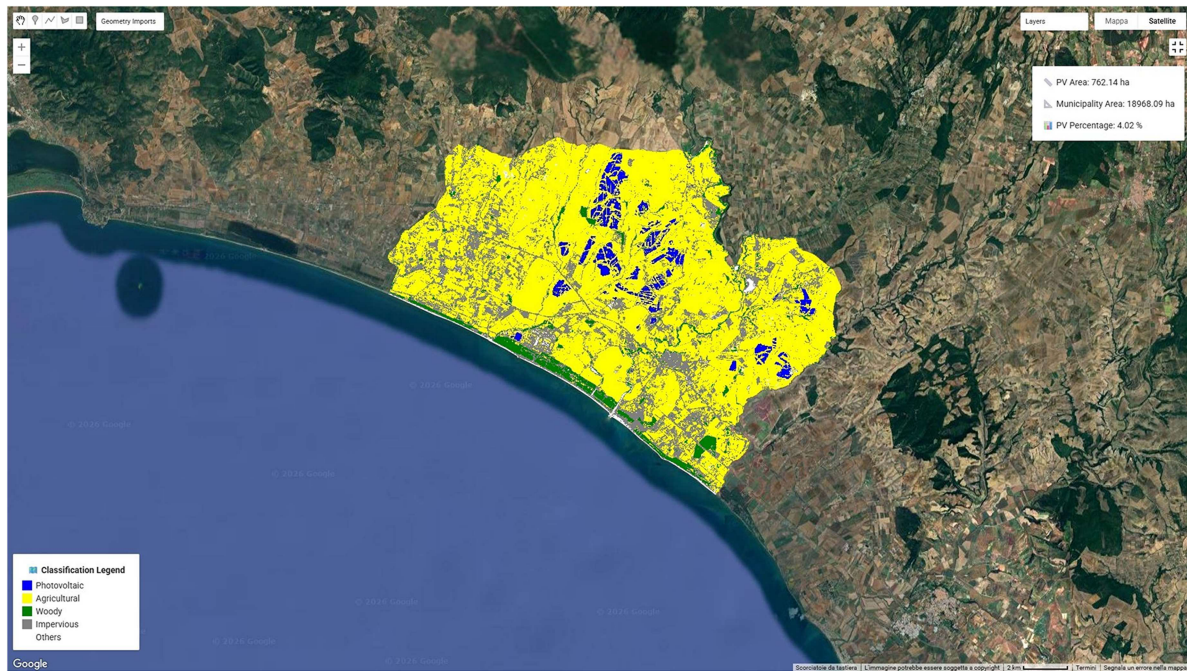


Figure 8. Classification map generated within the GEE application for the municipality of Montalto di Castro, based on Sentinel-2 imagery (July 2025) and Random Forest algorithm. The map displays the five land cover classes used in the analysis: Photovoltaic (blue), Agricultural (yellow), Woody vegetation (green), Impervious surfaces (grey), and Others (white). Summary statistics are shown in the top-right panel, and the classification legend is reported in the bottom-left corner.

allows for cross-validation of results and supports a more nuanced interpretation of land-use dynamics within PV footprints.

Because CLC + Backbone and EUCropMap are available for discrete reference years, the land-use reconstruction should be interpreted as a baseline snapshot within the footprint of PV mapped in the target year, rather than a definitive pre-installation state. Users can select alternative reference years (CLC + Backbone 2021; EUCropMap 2022) to reduce temporal mismatch, although some uncertainty remains where land use changed between the reference year and the installation period.

While both datasets are integrated in the GEE-based tool and support spatial masking of PV areas, our results are reported using a differentiated approach to reflect their structure and interpretative scope: CLC + Backbone values are expressed in hectares, emphasising the total surface area affected by land cover change; EUCropMap values are reported as percentages, highlighting the internal composition and relative frequency of crop types within PV-covered areas.

Land cover composition within PV areas based on CLC + Backbone 2018

The PV polygons derived from the Sentinel-2 classification were intersected with the CLC + Backbone 2018 dataset to assess land cover conditions prior to PV development. Land cover classes are shown in Figure 9 and results in Figure 10.

The analysis indicated that most PV installations replaced areas classified as periodically herbaceous (364.85 ha), followed by sealed surfaces (212.64 ha) and permanent herbaceous land (148.65 ha). Additional minor overlaps were recorded with non-vegetated land (6.65 ha) and various woody vegetation types, including broadleaved evergreen trees (0.01 ha), low-growing woody plants (0.02 ha). Although these latter values are negligible, all land cover classes detected within PV areas are reported for completeness.

As suggested by visual inspection of high-resolution imagery, CLC + Backbone does not distinguish between sealed artificial surfaces and PV panels. Consequently, the *sealed* class likely includes PV systems already installed before 2018, whereas other land cover types reflect land subsequently converted to PV.

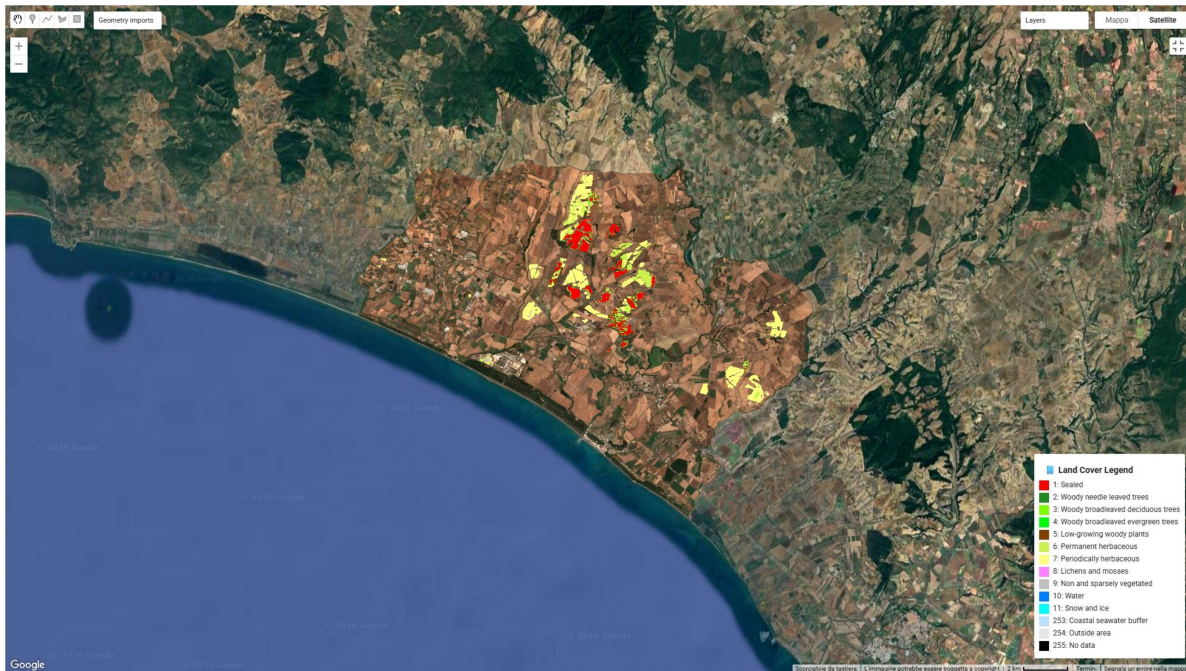


Figure 9. Land cover types (CLC + Backbone 2018) within areas classified as PV in Montalto di Castro. The map shows the result of masking the land cover dataset to the extent of PV polygons, highlighting only the land cover classes present within the detected PV areas. Colors correspond to the official CLC + Backbone legend.

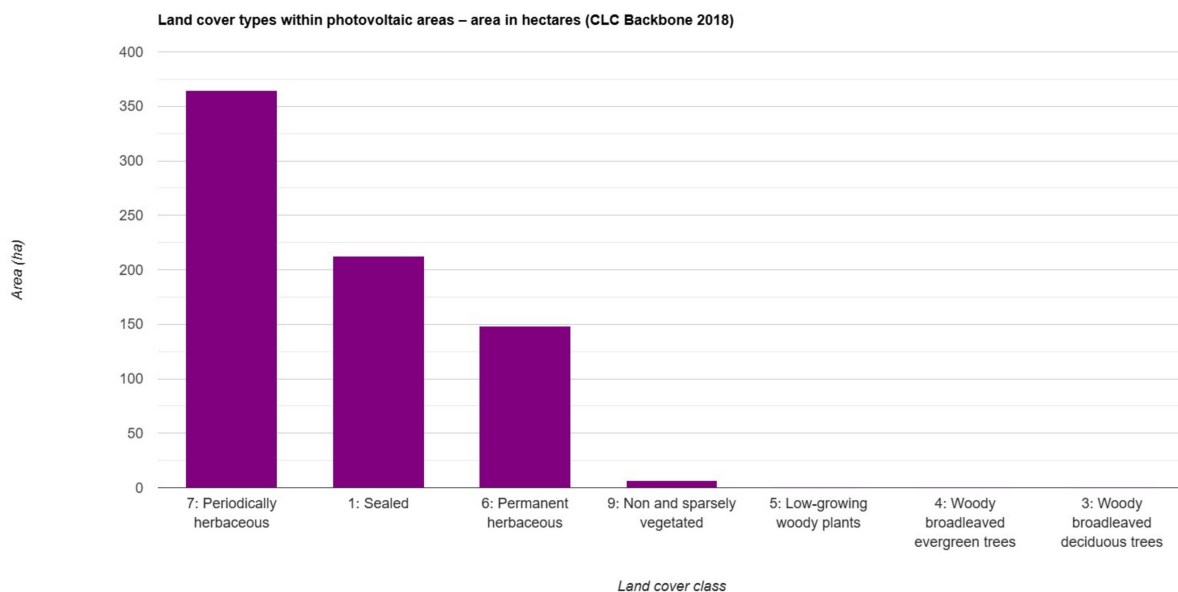


Figure 10. Bar chart showing the area (in hectares) of each land cover class found within PV polygons, based on CLC + Backbone 2018. The most frequent classes are 7 (Periodically herbaceous), 1 (Sealed), and 6 (Permanent herbaceous). Other classes (3, 4, 5, 10) show negligible values.

Crop type composition within PV areas based on EUCropMap 2018

To provide a more detailed picture of pre-existing agricultural land use, the PV polygons were intersected with the EUCropMap 2018 dataset, which represents the earliest available reference year and maximizes the temporal gap with the 2025 PV footprint. This allowed identification of the main crop types replaced by PV installations, based on annual declarations and satellite-derived classifications (Figure 11).

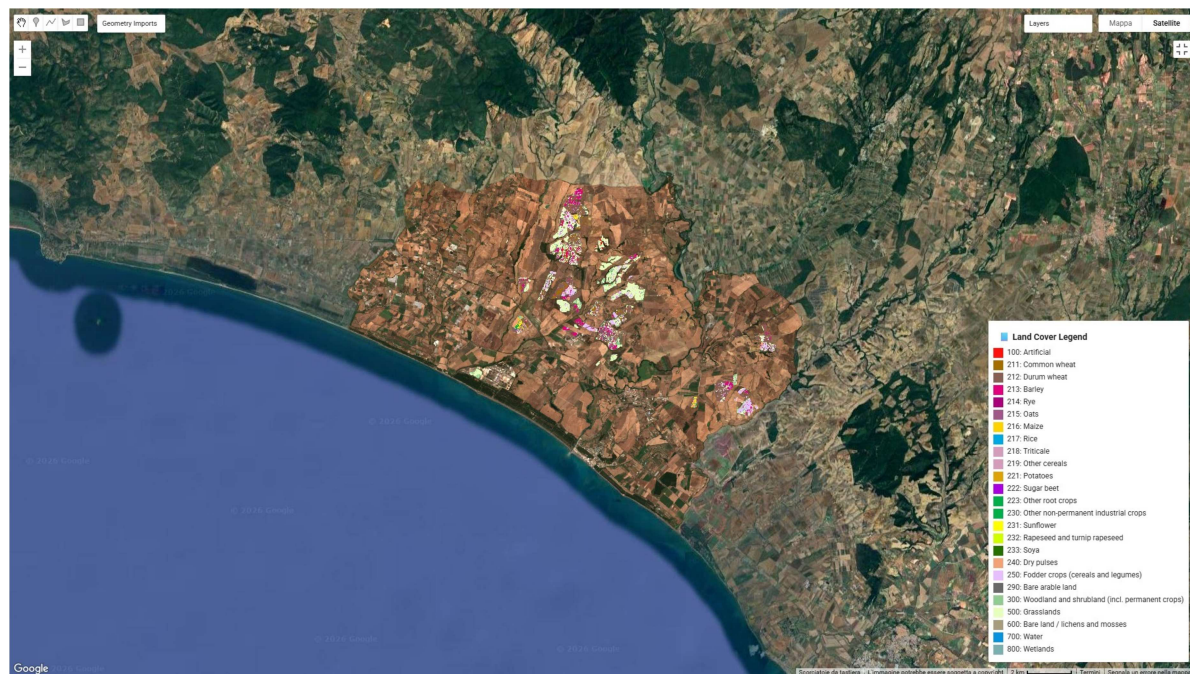


Figure 11. Map showing 2018 crop types within areas classified as PV in 2025 in Montalto di Castro. The EUCropMap 2018 dataset was masked to the extent of 2025 PV polygons, and only pixels within PV areas are displayed. The legend shows EUCropMap class codes and colours.

Proportion of land cover types within photovoltaic areas (%) – EUCropMap 2018

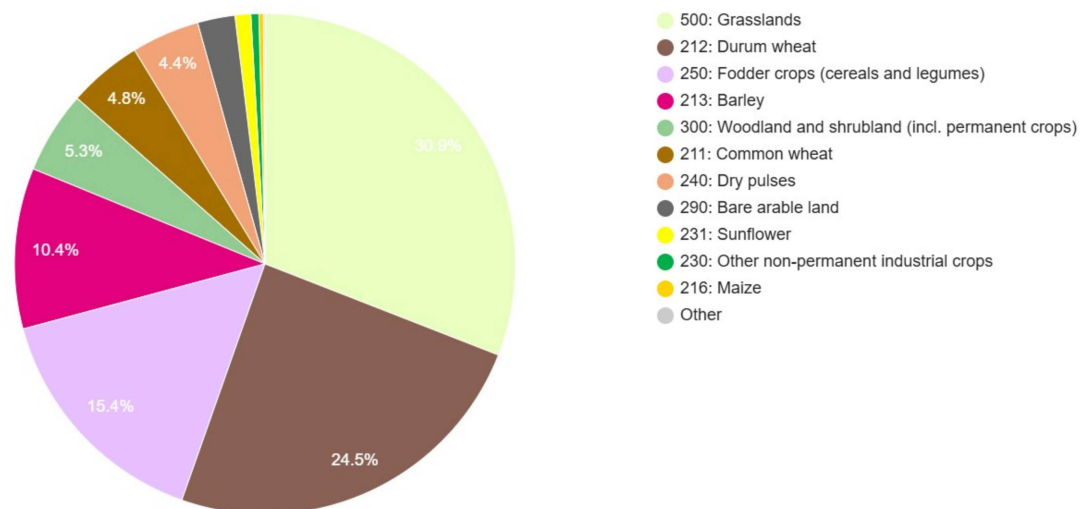


Figure 12. Pie chart illustrating the proportion of EUCropMap 2018 land cover classes within areas classified as ground-mounted PV in Montalto di Castro in 2025. Only crop types and surface categories intersecting the PV polygons are shown. Values are expressed as percentages of the total PV-covered area. Chart generated using the GEE-based tool.

The analysis showed that the most frequently represented categories were grasslands (30.93%), durum wheat (24.46%), fodder crops (15.43%), and barley (10.38%). Additional contributions came from common wheat (4.78%), dry pulses (4.38%), and bare arable land (2.42%). Minor shares were occupied by sunflower (1.02%), non-permanent industrial crops (0.51%), maize (0.29%), and oats (0.10%). A small proportion of the area (5.31%) was also mapped as woodland and shrubland, which may correspond to transitional vegetation, scattered permanent crops, or mixed-use parcels (Figure 12).

These results offer a more detailed, crop-level view of previous land cover within PV areas, expanding upon the broader categories identified in the CLC + Backbone analysis. However, due to differences in classification logic and observation methods, a direct correspondence between crop classes and land cover types is not always straightforward. A cross-dataset interpretation is therefore provided in [Land use insights and cross-dataset interpretation](#) (Discussion).

Cross-country applicability

To test the applicability of the workflow beyond the Italian context, the tool was applied in Spain, one of the European countries experiencing the fastest PV expansion (SolarPower Europe, 2024). The region of Andalucía was selected as one of Spain's main centres of PV growth, with 7,874 MW of installed capacity by December 2023 (REE – Red Eléctrica de España, 2024). Within it, the municipality of Guillena was chosen for its agricultural landscape and high density of ground-mounted PV systems, providing a suitable context to test the workflow under different administrative datasets. Guillena is located in the province of Seville, approximately 20 km north of the regional capital, and covers a total area of 226.79 km². The municipality is characterized by a Mediterranean climate with hot, dry summers and mild winters, supporting predominantly rainfed agriculture (cereals, olive groves) and extensive grazing. The workflow was executed without structural modifications, replacing only the Italian municipal boundary dataset (ISTAT – Istituto Nazionale di Statistica, 2025) with the Spanish administrative boundaries provided by the Centro Nacional de Información Geográfica (CNIG – Centro Nacional de Información Geográfica, 2025). Once the new FeatureCollection was uploaded and the corresponding Asset ID replaced within the script, the application automatically handled all subsequent steps, Sentinel-2 compositing, supervised classification, PV polygon extraction, and land-use analysis, following the same logic as in the Italian case study.

The analysis was performed using Sentinel-2 imagery acquired in July 2025, with a median composite and the CART classifier, which achieved the highest overall accuracy among the tested algorithms for this case study (87.62%; see Supplementary Table S3 for detailed classifier comparison).

The classification performance was assessed using the confusion matrix derived from the validation dataset (Table 2). Compared with the Montalto di Castro case study (overall accuracy = 91.05%), the slightly lower accuracy in Guillena is plausibly linked to site-specific conditions and image configuration (e.g. acquisition timing within the season, surface moisture and brightness, and the prevalence of bare or transitional surfaces), which may increase confusion particularly between agricultural, woody vegetation and impervious surfaces, and, to a lesser extent, between PV and agricultural/impervious areas. Importantly, this difference does not indicate reduced transferability: the workflow was transferred without structural changes, and the application allows users to adapt key settings (month, compositing reducer and classifier choice) through the interface to match local conditions. Therefore, when applying the tool to a new municipality, users can iteratively compare alternative configurations and select the most reliable output for their context, while keeping the overall workflow unchanged.

A total of 616.54 ha was identified as ground-mounted PV areas within the municipal boundaries, corresponding to approximately 2.72% of the municipal territory (Figure 13). These results confirm the robustness and stability of the workflow when applied to different national contexts. According to the *Informe de Infraestructuras Energéticas de Andalucía* (Agencia Andaluza de la Energía, 2025), Guillena hosts eleven large-scale photovoltaic plants exceeding 10 MW each, with a combined installed capacity of approximately 545 MW. Although the report does not provide an explicit estimate of occupied land area,

Table 2. Confusion matrix for the municipality of Guillena (Andalucía, Spain). Rows represent actual classes; columns represent predicted classes.

Actual	Predicted				
	Photovoltaic (0)	Agricultural (1)	Woody (2)	Impervious (3)	Others (4)
Photovoltaic (0)	1489	126	0	94	0
Agricultural (1)	2	10002	1133	866	0
Woody (2)	0	220	6055	2	0
Impervious (3)	80	504	36	2487	2
Others (4)	2	3	24	1	1876

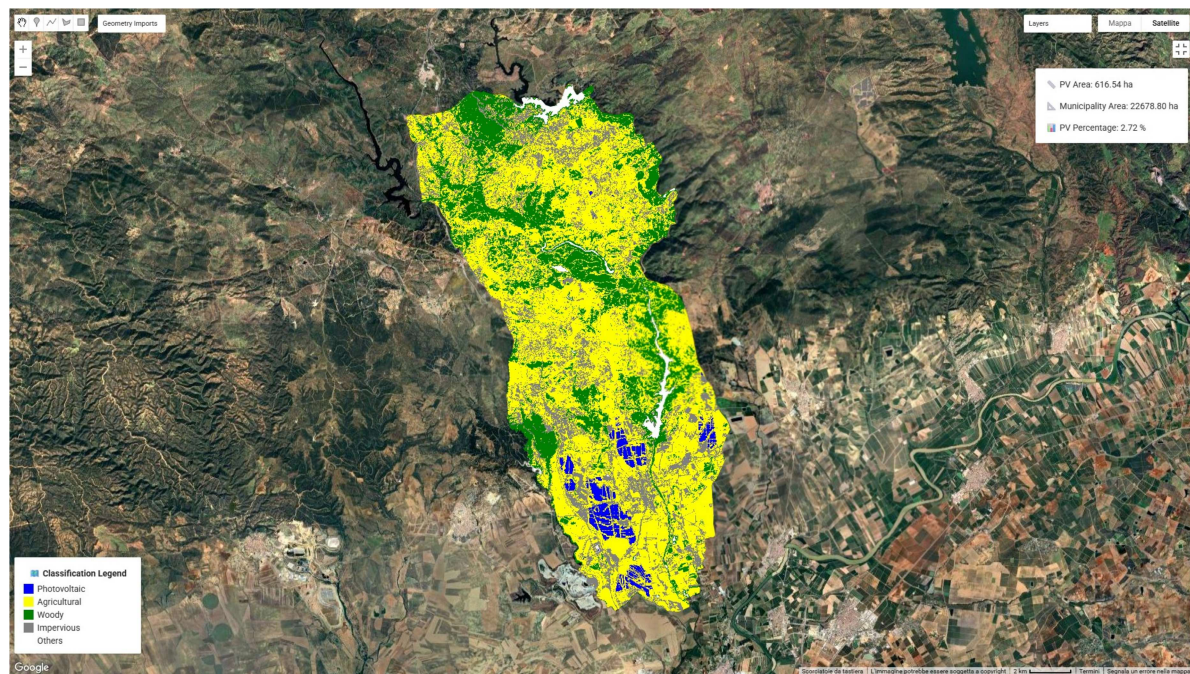


Figure 13. Classification map generated within the GEE application for the municipality of Guillena (Andalucía, Spain), based on Sentinel-2 imagery (July 2025, median composite) and the CART classifier. The map displays the five land-cover classes used in the analysis: Photovoltaic (blue), Agricultural (yellow), Woody vegetation (green), Impervious surfaces (grey), and Others (white). Summary statistics are shown in the top-right panel, and the classification legend is reported in the bottom-left corner.

capacity-based conversions should be interpreted cautiously, as land-take per MW varies widely with technology, layout and terrain. Nonetheless, a typical indicative range of $\sim 1\text{--}2$ ha per MW for utility-scale PV (Bolinger & Bolinger, 2022) implies an order of magnitude of $\sim 545\text{--}1,090$ ha, which is broadly consistent with our mapped extent (616.54 ha). This agreement should be considered indicative rather than a validation, as the mapped area depends on the classification output and the definition of PV footprints (e.g. inclusion/exclusion of internal roads and spacing).

In this case, no parameter adjustments were required, as Guillena presented a relatively homogeneous landscape. However, for larger or more heterogeneous municipalities, users may need to increase the number of training and validation polygons and/or refine the predefined land-cover classes (e.g. subdividing agricultural or impervious categories) to better capture spectral variability and maintain classification accuracy across complex landscapes.

A continent-wide alternative is offered by the Eurostat administrative boundaries dataset at LAU level (Local Administrative Units), which corresponds to municipalities or equivalent local divisions across EU Member States (Eurostat – GISCO, 2024). This dataset enables the workflow to be applied consistently at municipal scale throughout Europe, although its spatial precision is generally lower than that of national datasets such as ISTAT or CNIG. An example of the selection of a European municipality using this dataset is shown in Figure 14, while detailed instructions for integrating Spanish and European boundary datasets are available in the supplementary documentation on Zenodo (Cotti Piccinelli et al., 2025a).

Overall, this test demonstrates that the proposed GEE application is not limited to Italy but can be readily adapted to other countries with minimal preprocessing effort.

Discussion

Land use insights and cross-dataset interpretation

Despite differences in classification logic and thematic resolution, CLC + Backbone and EUCropMap provide convergent evidence on the land-use context of PV deployment in Montalto di Castro. Most of the 2025 PV



Figure 14. Example of European-scale application of the GEE app using the Eurostat- Local Administrative Units dataset. The figure shows the selection of the municipality of Medemblik (Netherlands) within the app interface. This area includes the locality of Andijk, which hosts one of the largest floating PV in Europe, built on 15 artificial islands.

footprint overlaps land classified as periodically herbaceous in CLC + Backbone 2018 (364.85 ha), which is consistent with rotational crops or temporary forage. EUCropMap supports this pattern by showing a prevalence of durum wheat (24.46%), barley (10.38%), and fodder crops (15.43%), all characteristic of short-cycle arable systems. The permanent herbaceous class in CLC + Backbone, though less extensive (148.65 ha), is consistent with the prominence of parcels labelled as grasslands (30.93%) in EUCropMap. However, such areas may include forage production systems, managed grasslands, or set-aside parcels, and may have been classified as periodically herbaceous if subject to disturbances such as reseeding or ploughing during the reference year (EEA – European Environment Agency, 2023). Taken together, these findings indicate that approximately 70% of the land cover within the 2025 PV footprint was classified as herbaceous in CLC + Backbone 2018 (periodically + permanent herbaceous), supporting a consistent association with arable/forage land types also highlighted by EUCropMap. This convergence across datasets indicates a strong correspondence between detected PV areas and herbaceous agricultural land types captured by CLC + Backbone and EUCropMap. This outcome aligns with national-scale patterns observed by Delfanti et al. (2016), who showed that PV deployment in Italy has often targeted accessible, low-elevation rural areas under cultivation, contributing to land take and pressure on traditional agricultural systems (Delfanti et al., 2016). Although woody vegetation was almost entirely avoided (0.03 ha in CLC + Backbone; 5.31% in EUCropMap, where class 300 also includes scattered trees and permanent crops), the loss of herbaceous farmland is not ecologically neutral. Croplands and grasslands support biodiversity and ecosystem services such as pollination, pest control, and landscape connectivity (Kleijn et al., 2006; Tscharntke et al., 2005), yet this ecological value is often underestimated in Environmental Impact Assessments (Alcione, 2022; Iberdrola Renovables Italia S.p.A., 2022; SolarFieldsSette S.r.l., 2023). However, PV systems can be designed to integrate biodiversity-supporting features, transforming conflicts into multifunctional systems (Cotti Piccinelli et al., 2025b; Nordberg et al., 2021).

This vision is echoed in recent Italian policy, which promotes agrivoltaics as a strategy to limit land take on fertile soils (MASE – Ministero dell’Ambiente e della Sicurezza Energetica, 2024) and in earlier proposals highlighting the potential of dual-use approaches (Barron-Gafford et al., 2019; Dupraz et al., 2011). However, our results indicate that the recent expansion of ground-mounted PV in Montalto di Castro has predominantly occurred on productive herbaceous farmland, rather than on marginal or degraded land (REPowerEU, 2022). This finding challenges the narrative of “low-impact deployment” promoted in national and European policy frameworks (MASE – Ministero dell’Ambiente e della Sicurezza Energetica, 2024; REPowerEU, 2022), highlighting instead a tangible trade-off between renewable energy development and the maintenance of agricultural functions. Such evidence calls for a critical

rethinking of PV siting and design strategies, moving beyond mitigation principles towards multi-functional configurations that actively sustain agroecological processes and rural economies.

Within this perspective, ground-mounted PV systems could be reframed as part of integrated Nature-based Solutions, provided that their spatial design and management explicitly incorporate biodiversity-supporting features, soil conservation measures, or productive understorey practices. The present study thus contributes empirical evidence that underpins and operationalises the conceptual framework proposed by Cotti Piccinelli (2025b), which advocates for PV systems designed to simultaneously generate renewable energy, preserve farmland functions, and deliver ecosystem services.

Spatial clustering and cumulative impact

The case study confirms the strategic relevance of Montalto di Castro within the context of large-scale PV deployment in Viterbo province and the Lazio region.

According to national statistics, Lazio accounted for approximately 1,527 ha of land occupied by ground-mounted PV systems in 2023, ranking third nationally after Apulia and Sicily (GSE – Gestore dei Servizi Energetici, 2024). While GSE data are primarily aggregated at the regional level, the 2023 report also identifies Montalto di Castro among the Italian municipalities exceeding 300 ha of ground-mounted PV, confirming its prominent role in national PV development. Using a Sentinel-2 monthly composite for July 2025, our GEE tool estimated 762.14 ha of ground-mounted PV from the raw classification output within the municipal boundaries. Although referring to two years later, this value supports the evidence of continued PV expansion and confirms the municipality's exceptionally high concentration of installations, accounting for approximately ~49.9% of the total PV-related land use reported for Lazio in 2023 (1,527 ha).

To verify the consistency of our method, we also tested the tool using Sentinel-2 imagery from July 2023 with a minimum reducer. The resulting classification output is shown in Figure S1 (Supplementary Material). This test detected 298.37 ha of PV with an overall accuracy of 91.88%, which is close to the GSE threshold used to flag municipalities with more than 300 ha of ground-mounted PV by the end of 2023. These results support the coherence between our remote-sensing-based approach and official statistics, while also demonstrating the tool's ability to track PV expansion through time. Detailed accuracy metrics, the confusion matrix (Table S4), and the sensitivity analysis (Table S5) are reported in the Supplementary Material.

These outputs raise important spatial planning considerations. On the one hand, Montalto di Castro benefits from pre-existing energy infrastructure, including a robust electricity grid originally built for a now-decommissioned thermoelectric plant (ANSA, 2022), potentially justifying concentrated PV deployment in suitable energy corridors. On the other hand, such spatial concentration may increase the risk of cumulative environmental impacts, especially when multiple adjacent projects are approved without integrated assessment. Cumulative effects remain poorly addressed in Italian EIA for renewable energy projects: reviewed documents for Montalto di Castro mention “cumulative impact” analysis but limit it to spatial mapping of nearby installations without actual assessment (Alcione, 2022; Energia Ecosostenibile S.r.l., 2023; SolarFieldsSette S.r.l., 2023), a gap documented at national level by Rosnati and Corbia (2014).

Their work highlighted the lack of strategic planning and the fragmentation between planning levels, advocating for the systematic application of Cumulative Effects Assessment in regional and municipal energy strategies (Rosnati & Corbia, 2014). The authors demonstrated, through a case study in Sassari (Sardinia), how uncoordinated project-level authorisations can lead to widespread land conversion and landscape transformation, in contrast with local goals of minimising environmental impacts and supporting small-scale, locally integrated renewable systems (Rosnati & Corbia, 2014).

This lack of cumulative assessment is not unique to Italy. A recent study examining the spatial distribution of PV and wind power plants in Poland similarly underlined the absence of regional-scale evaluations capable of capturing cumulative pressures (Pelczar, 2025). The author emphasises that while GIS-based tools and multi-criteria decision-making methods were increasingly used to identify suitable sites, these technical approaches often overlooked the broader environmental consequences of spatial clustering. In both cases, the findings suggested that spatial planning for renewables must go beyond

site-level optimisation and incorporate cumulative and systemic impacts across scales (Pelczar, 2025; Rosnati & Corbia, 2014).

These insights suggest a key trade-off between spatial concentration and dispersal: focusing solar development in already equipped hubs like Montalto di Castro could limit grid expansion and streamline approvals but may amplify local ecological pressures. Conversely, spreading PV systems more evenly might reduce localised impacts, but result in broader land take and new infrastructure needs. Building on Hermoso et al. (2023) scenario-based optimisation, a first step should be to incorporate an empirical baseline of where PV already exists, precisely what our GEE tool provides, so that zoning alternatives are tested against the current spatial footprint and not only theoretical suitability (Hermoso et al., 2023). Using this baseline, planners can evaluate zoning rules that explicitly account for existing clusters, grid availability, and ecological sensitivities. This would allow comparison of cluster-anchored versus dispersal-oriented distributions, and hybrid variants, under realistic constraints, helping identify the zoning configuration that best balances production targets with limits on agricultural conversion and cumulative biodiversity pressures (Hermoso et al., 2023).

In this perspective, a more balanced and informed planning approach is needed, one that favours the development of energy clusters conceived as multifunctional systems, where renewable energy production is designed and managed to maintain or enhance biodiversity and ecosystem services (Carvalho et al., 2023; Cotti Piccinelli et al., 2025b; Hermoso et al., 2023). Several studies have demonstrated that ground-mounted PV can deliver environmental co-benefits, such as pollinator support, improved soil moisture, enhanced crop productivity in agrivoltaic systems, and microclimate regulation (Barron-Gafford et al., 2019; Blaydes et al., 2021; Tanner et al., 2020).

Taking this further, Semeraro et al., (2018, 2022) proposed that PV farms designed with biodiversity in mind can actively support ecological networks and suggested clustering rules informed by pollinator movement ranges as a planning hypothesis to delineate potential ecosystem-service zones (Semeraro et al., 2022). At the same time, recent evidence cautions against using *Apis mellifera* as a universal proxy for pollinator diversity: managed honeybees may compete with wild bees and alter plant–pollinator network structure (Mallinger et al., 2017; Page & Williams, 2023; Valido et al., 2019). Moreover, many wild bee species forage over shorter distances than managed honeybees, implying that broad-scale clustering alone may be insufficient and that within-site habitat provision and heterogeneity are likely to be critical (Connop et al., 2011; Gathmann & Tschardt, 2002; Zurbuchen et al., 2010). In this sense, PV landscapes may require biodiversity-oriented designs that integrate microhabitats within and around installations rather than relying solely on broad-scale clustering.

In this light, it is necessary to further investigate whether biodiversity-oriented management strategies can genuinely enhance habitat continuity for metapopulation-based species; species composed of distinct but interlinked populations connected by occasional dispersal (Hastings & Harrison, 1994; Nee, 2007). This challenge extends beyond pollinators to other taxa potentially affected by PV infrastructure and mitigation measures, such as wildlife-friendly fencing (Bennun et al., 2021; Cotti Piccinelli et al., 2025b), highlighting the need for integrated ecological assessments capable of capturing multi-species connectivity across PV landscapes (Gómez-Catasús et al., 2024). Here, the tool contributes by providing the spatial baseline (PV footprints and clustering patterns) needed to support such analyses, rather than by assessing ecological outcomes directly.

Tool relevance, applicability, and planning implications

The application developed in this study provides an operational, replicable tool to support spatial assessments of ground-mounted PV systems in Italy, particularly with respect to land-use change. Unlike previous Italian models centred on ex-ante suitability under legal, technical, or economic constraints (Fattoruso et al., 2024; Sacchelli et al., 2016), our approach detects existing PV installations from satellite imagery, enabling data-driven retrospective and ongoing monitoring at municipal level.

Compared with other methodologies (e.g. Tao et al., 2023), which combine object-based segmentation and manual validation but do not differentiate rooftop from ground-mounted PV and require substantial expertise, our GEE app uses a user-friendly workflow that excludes rooftops through geometric filtering

and applies a MMU to remove small areas that cannot reasonably be considered ground-mounted installations.

Our tool operates on two complementary levels. First, it delivers immediate, in-app insight at the municipality scale: users can directly read the share of municipal area occupied by PV (in hectares and percentage) and view pre-installation land use through bar and pie charts. These outputs provide a rapid appraisal of PV footprint and prior land use, suitable for quick screening and communication without requiring additional software. Second, the tool supports extended analyses beyond the app by exporting PV polygons, classified surface rasters, and associated summary tables in standard formats (e.g. Shapefile/GeoJSON and GeoTIFF), enabling direct use in desktop and web-based GIS environments (e.g. QGIS, ArcGIS Pro, ArcGIS Online or regional webGIS portals). This interoperability enables routine downstream operations outside the tool, such as intersecting PV polygons with zoning layers, calculating affected surface areas by planning unit, overlaying PV footprints with environmental constraints, and preparing cartographic annexes and summary tables for planning documents and environmental reporting.

A practical example is municipal screening of new utility-scale PV or agrivoltaic proposals. By using the exported PV polygons, planning staff can quantify existing cumulative land take within the relevant zoning unit, identify spatial clustering and hotspot areas, and overlay installations with key constraints (e.g. protected areas, landscape designations, cultural heritage buffers) to flag potential conflicts early in the permitting process. In parallel, the land-use forensic output, linking PV footprints to prior land cover (and crop categories where available), can support contextual reporting within zoning updates or EIA scoping and alternatives assessment, by documenting what land uses have been converted and helping frame design discussions aimed at maintaining agricultural functionality. Crop selection and agronomic feasibility remain site-specific and should be verified through dedicated surveys; therefore, the tool is intended to complement, rather than replace, detailed EIA studies.

More broadly, PV planning in Italy should move beyond opportunistic siting by private developers towards coordinated spatial planning that promotes co-development and collaboration among energy companies, local institutions, and communities. In this context, our tool helps bridge high-level policy frameworks and local spatial realities: its accessibility, modularity, and reliance on open geospatial datasets make it suitable for authorities, planners, and researchers with limited technical resources. By enabling direct comparison of land-use conditions before and after PV deployment, it supports evidence-based decisions and more transparent land governance. Further research should integrate land-use monitoring with economic, technical, and legal assessments (Fattoruso et al., 2024), as well as with spatial analyses that explicitly account for agricultural value and biodiversity conservation priorities (Hermoso et al., 2023), in order to support truly holistic and sustainable PV planning.

Because the script is public, users can also adjust the spatial scale or study region and integrate context-specific datasets, leveraging free platforms like GEE and open satellite data.

Limitations and future research directions

Although the workflow demonstrated robust classification performance and cross-country applicability, several aspects warrant further development.

First, the current implementation relies on optical Sentinel-2 predictors and does not explicitly account for terrain effects. In many cases, utility-scale ground-mounted PV is installed on relatively flat terrain, as steep-slope construction often requires levelling and may increase soil disturbance and infrastructure costs; consequently, terrain-shadow artefacts are expected to be limited in typical target settings. Nevertheless, in high-relief municipalities, topographic shadows can locally resemble the spectral response of dark PV surfaces, potentially increasing confusion with PV in rugged or highly heterogeneous landscapes. Future versions could integrate Digital Elevation Model (DEM) derivatives (e.g. slope, aspect, hillshade) as additional predictors or apply terrain-aware masking/correction steps to improve robustness and applicability in mountainous contexts, where topographic effects and complex terrain can affect classification performance (Orusa et al., 2023b).

Second, although the workflow demonstrated robust classification performance across both case studies, with overall accuracy of 91.05% for Montalto di Castro (July 2025, Random Forest; Table 1) and 87.62% for Guillena (July 2025, CART; Table 2), accuracy may vary depending on the size and heterogeneity of the

selected municipality, the quality and representativeness of training polygons, and the seasonal timing of Sentinel-2 composites. An additional consistency check using July 2023 imagery with a minimum reducer for Montalto di Castro (Figure S1; Table S4, Table S5) yielded 91.88% overall accuracy, demonstrating temporal stability of the classification approach.

To address this operational variability, the application is designed to support user-led sensitivity testing. Users can compare different compositing months and reducers, switch between classification algorithms, and increase the number and spatial representativeness of training and validation polygons when working in more heterogeneous landscapes. This design choice helps maintain usability and applicability while enabling targeted optimization under local conditions. Moreover, while the current workflow allows multi-algorithm comparison, it does not automatically optimize classifier parameters or sampling balance, which may affect cross-site consistency. Future developments could therefore integrate probabilistic (e.g. stratified random) validation sampling and semi-automated parameter tuning to further strengthen the methodological rigour and scalability of the tool.

Third, the adoption of a 0.50 ha minimum mapping unit (MMU) reflects a deliberate focus on utility-scale ground-mounted PV farms and supports spatial filtering by removing small, fragmented objects and spurious detections. Sensitivity testing (Table S1, Supplementary Material) showed that lowering the MMU to 0.10–0.25 ha increased the number of detected polygons but altered total mapped PV area by <1%, indicating that the selected threshold primarily affects object fragmentation rather than overall extent in the tested context. Nonetheless, the 0.50 ha MMU can under-detect smaller or dispersed ground-mounted installations, particularly in fragmented landscapes or where community-scale systems are relevant. Future implementations could therefore include user-selectable or adaptive MMU settings, explicitly aligned with monitoring objectives (e.g. utility-scale screening vs completeness for small installations), while maintaining a clear separation from rooftop PV.

Fourth, the tool does not quantify ecological outcomes and cannot, on its own, support causal claims about biodiversity impacts. Its primary contribution is to provide spatially explicit PV footprints, clustering patterns and baseline land-use information that enable downstream ecological and planning analyses. For example, exported PV polygons can be coupled with established landscape connectivity frameworks (e.g. graph-based or circuit-theory approaches) to test how alternative siting rules, clustering patterns and mitigation layouts may influence habitat permeability and corridor continuity (McRae et al., 2008; Saura & Pascual-Hortal, 2007). In parallel, future versions could integrate optional screening modules within the GEE interface, including automated overlay with protected areas (e.g. Natura 2000; European Commission, 2024), proximity analysis to ecological infrastructure, and land-use-based biodiversity metrics (e.g. Mean Species Abundance; Alkemade et al., 2009), intended for early-stage appraisal and to be complemented by site-specific surveys and detailed connectivity modeling.

Fifth, land-use reconstruction is constrained by the discrete reference years of CLC + Backbone and EUCropMap, which may introduce temporal mismatch when PV is mapped in later years. Future work will explore annual land-cover products (e.g. Dynamic World) to strengthen temporal alignment.

An additional technical frontier concerns distinguishing conventional ground-mounted PV from agrivoltaic configurations, where elevated structures enable continued agricultural production and entail different land-use and ecological implications. Future developments should aim to discriminate these typologies by integrating complementary sensors and reference data. In particular, Sentinel-1 Synthetic Aperture Radar (SAR) may be valuable because radar backscatter is sensitive to structural characteristics and could help detect elevated mounting systems and related spatial patterns that optical imagery alone may not fully resolve.

Finally, the application is currently undergoing end-user testing with Infrastrutture S.p.A. staff to gather feedback on usability, workflow clarity and operational requirements; this will support iterative improvements to the interface and, where appropriate, to classifier configuration and accuracy across target contexts.

Conclusion

This study presented an open-access application developed in Google Earth Engine for detecting existing PV installations and reconstructing associated land-use change through the integration of Sentinel-2 imagery, CLC + Backbone, and EUCropMap datasets.

The application enabled the identification and quantification of PV systems in Montalto di Castro, providing both spatial outputs and land-use information linked to the detected PV footprint. Results indicated that a large proportion of the areas occupied by PV installations corresponded to herbaceous and agricultural land-cover classes, highlighting the relevance of agricultural landscapes in recent PV expansion dynamics.

The workflow also proved adaptable beyond the Italian context through its application to Guillena (Spain), requiring only limited modifications related to administrative datasets. This demonstrates the potential of the tool for comparative analyses of PV deployment and land-use change across different European contexts.

The application supports spatial planning by providing exportable PV footprints, land-use reconstruction, and summary statistics for integration with territorial analysis workflows.

Future developments should focus on improving temporal alignment between baseline land-use layers and installation periods, integrating terrain-related predictors for high-relief areas, refining the detection of small installations through adaptive MMU settings, and exploring the distinction between conventional PV and agrivoltaics systems through the integration of additional data sources such as Sentinel-1 SAR.

Author contributions

CRediT: **Marta Cotti Piccinelli**: Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Caroline Nash**: Supervision, Writing – review & editing; **Stuart Connop**: Conceptualization, Supervision, Visualization, Writing – review & editing; **Marco Ciolfi**: Conceptualization, Data curation, Formal analysis, Methodology, Software, Supervision, Writing – original draft; **Carlo Calfapietra**: Supervision, Writing – review & editing; **Chiara Baldacchini**: Conceptualization, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Data availability statement

The data that support the findings of this study are openly available in Zenodo at <https://doi.org/10.5281/zenodo.17303773>.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT to improve the readability of the text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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