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AI and GIS Modelling for Agrivoltaic Deployment in Ukraine

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SUMMARY

Agrivoltaics can support Ukraine's post-war energy reconstruction by combining distributed solar generation with continued agricultural land use. This is particularly relevant for communities affected by war damage, where energy resilience, rural recovery, and preservation of productive soils must be addressed simultaneously. This study develops a reproducible AI-GIS screening workflow for preliminary agrivoltaic suitability modelling in the Borodianka Territorial Community, Kyiv Oblast, Ukraine. The workflow integrates open geospatial datasets, QGIS-compatible preprocessing, GIS multicriteria decision analysis, and Random Forest classification. A baseline suitability model was produced using COD-AB administrative boundaries and OpenStreetMap layers, including roads, power infrastructure, water bodies, buildings, protected areas, and land-use polygons. The baseline GIS-MCDA model identified 52.19 km2 as highly suitable and 155.87 km2 as moderately suitable for further assessment. A Random Forest classifier trained on expert-rule MCDA labels identified 54.18 km2 as highly suitable and 152.61 km2 as moderately suitable. The model is interpreted as a screening-level decision-support prototype rather than an engineering design. The study demonstrates that open AI-GIS workflows can support early-stage spatial planning of agrivoltaics, while also revealing major barriers: incomplete land-use and cadastral data, limited power-grid information, absence of grid-capacity data, lack of soil and crop-rotation layers, DEM and satellite-resolution limitations, war-related land risks, and the absence of dedicated Ukrainian agrivoltaic standards.

Keywords: agrivoltaics; GIS; Random Forest; land suitability; post-war reconstruction; distributed generation; Ukraine; QGIS; geodetic accuracy

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Introduction

Ukraine's post-war recovery requires energy solutions that improve local resilience without intensifying land-use conflicts. Wartime attacks have demonstrated the vulnerability of centralized energy infrastructure, while distributed renewable generation can support community-level resilience and reduce dependence on large energy nodes (International Energy Agency, 2024). At the same time, Ukraine's agricultural land, including highly productive chernozem soils, is a strategic national resource. Conventional ground-mounted photovoltaic development may compete with agricultural production, especially in rural communities where farming remains central to economic recovery.

Agrivoltaics offers a possible compromise by combining photovoltaic electricity generation and agricultural production on the same land; European agrivoltaic practice also emphasizes the preservation of primary agricultural use in such systems (DIN Media, 2021; Fattoruso et al., 2024). In this study, agrivoltaics is considered not only as an energy technology but also as a spatial planning problem. The key question is whether open geospatial data, GIS analysis, and machine learning can provide a reliable preliminary assessment of agrivoltaic suitability in a Ukrainian recovery community.

The Borodianka Territorial Community in Kyiv Oblast was selected as a pilot area because it has documented war damage, an active recovery context, agricultural land resources, and better public data availability than many territories closer to the active front line (United Nations Development Programme in Ukraine, 2025). The study aligns with GeoTerrace topics related to post-war reconstruction, remote sensing and GIS, digital agricultural planning, decision-support systems, and geodetic data quality (European Association of Geoscientists and Engineers in Ukraine, 2026; OpenReviewHub, 2026).

The market and ecological relevance of this topic is connected with the need to combine energy security, rural recovery, and protection of agricultural productivity. For Ukrainian communities affected by war, distributed solar generation can reduce dependence on vulnerable centralized infrastructure and support local electricity supply. However, large conventional solar farms may create pressure on agricultural land. Agrivoltaic systems offer a more balanced option because the same area can remain in agricultural use while also producing renewable electricity. This is especially important for Ukraine, where fertile soils and food production are strategic resources in the post-war recovery process.

Method and Theory

The proposed workflow combines GIS-based multicriteria decision analysis and machine learning. GIS-MCDA is widely used for spatial suitability problems, while open-source Python workflows support reproducible land-use suitability modelling (Malczewski, 2006; Chen, Judge, & Hulse, 2022). The current prototype uses open data sources that can be reproduced in QGIS and Google Colab/Python environments. The area of interest was defined using the COD-AB administrative boundary for the Borodianka Territorial Community. OpenStreetMap data were extracted for roads, power infrastructure, water bodies, buildings, protected areas, and land-use polygons. All layers were harmonized to EPSG:32635 before rasterization, distance calculation, and area estimation.

The selected open-data approach is also important from a reproducibility perspective. The workflow can be repeated in QGIS and Python/Colab using publicly available administrative and OpenStreetMap layers. This makes the method useful for early-stage community planning, especially when local authorities or researchers do not yet have access to complete engineering, cadastral, or grid-operator datasets. At the same time, this reproducibility is achieved at the cost of lower thematic and positional certainty. Therefore, the model is designed as a transparent screening tool that shows where more detailed data collection should start.

The baseline GIS-MCDA model was implemented at 30 m raster resolution, following the general logic of spatial multicriteria suitability analysis used in land-use and agrivoltaic eligibility studies (Malczewski, 2006; Fattoruso et al., 2024). Suitability criteria included an agricultural land-use proxy, distance to power infrastructure, distance to roads, distance from buildings, and distance from water bodies. Exclusion criteria included water bodies, building locations and near-building buffers, protected areas, forest land-use polygons, and incompatible land uses such as residential, industrial, commercial, military, quarry, and cemetery areas. Each criterion was transformed to a normalized 0-1 suitability score. The baseline suitability index was calculated as:

$$S = 0.35 \cdot C_{agri} + 0.25 \cdot C_{power} + 0.15 \cdot C_{road} + 0.15 \cdot C_{settlement} + 0.10 \cdot C_{water}$$

where C_agri represents the agricultural land-use proxy, C_power represents suitability by proximity to mapped power infrastructure, C_road represents road accessibility, C_settlement represents distance from buildings, and C_water represents distance from water bodies. The resulting continuous score was classified into four classes: unsuitable/excluded, low suitability, moderate suitability, and high suitability.

A Random Forest classifier was then trained using the GIS-MCDA classes as expert-rule labels. In the local prototype, the predictor set included agricultural and forest land-use proxies, incompatible land-use masks, protected-area masks, distance to roads, distance to power infrastructure, distance to water, distance to buildings, and normalized road, power, settlement, and water suitability scores. This AI-GIS workflow follows the reproducible suitability-modelling rationale described by Chen, Judge, and Hulse (2022) The Random Forest model used 400 trees, balanced class weights, and stratified train-test splitting. Feature importance was extracted to identify the strongest spatial drivers of modelled suitability.

The current workflow is intentionally treated as a screening-level prototype. It demonstrates the AI-GIS modelling logic, but it does not replace engineering design. Accurate assessment requires Sentinel-2 imagery, terrain data, cadastral parcels, soil quality, grid capacity, and war-related risks.

From a geodetic point of view, the model highlights the difference between planning-level suitability mapping and engineering-level site assessment. Harmonizing layers in a projected coordinate reference system is sufficient for preliminary distance and area calculations, but it is not enough for the design of panel rows, foundations, drainage, service roads, and agricultural machinery movement. A future engineering stage would require higher-resolution topographic survey, verified parcel boundaries, reliable vertical reference control, and consistency with Ukrainian and European height systems.

Results

The baseline OSM-MCDA model identified approximately 278.46 km2 as unsuitable or excluded, 29.26 km2 as low suitability, 155.87 km2 as moderate suitability, and 52.19 km2 as high suitability. The Random Forest prototype produced a similar spatial pattern, classifying 276.18 km2 as unsuitable or excluded, 32.80 km2 as low suitability, 152.61 km2 as moderate suitability, and 54.18 km2 as high suitability (Figure 1).

The similarity between the GIS-MCDA and Random Forest outputs is expected because the initial training labels were derived from the MCDA model. However, the Random Forest output is still useful for testing the integration of machine learning into the GIS workflow and for identifying which predictors drive the classification. In the current prototype, the most influential predictors were the forest proxy, agricultural land-use proxy, water-distance variables, road accessibility, settlement/building distance, and power-infrastructure proximity.

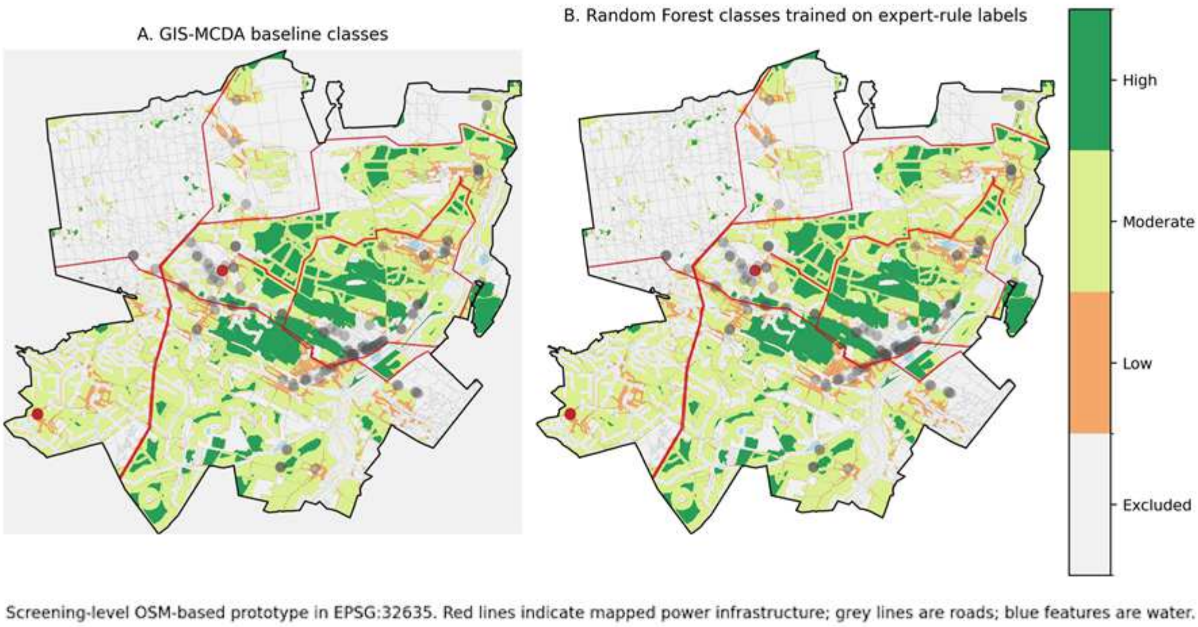

Figure 1. *Preliminary agrivoltaic suitability modelling for the Borodianka Territorial Community. Panel A shows the GIS-MCDA baseline classes derived from open OSM/COD-AB data. Panel B shows the Random Forest classification trained on expert-rule MCDA labels. The figure is interpreted as a screening-level AI-GIS result rather than an engineering site-selection map.*

The results show that even a simple open-data workflow can identify spatially coherent zones for further agrivoltaic assessment. At the same time, the modelling process exposes key barriers. OpenStreetMap land-use data are incomplete and cannot substitute for cadastral or detailed agricultural land data.

The absence of a dedicated Ukrainian agrivoltaic standard is another practical barrier. European documents such as DIN SPEC 91434 provide a useful benchmark because they define agrivoltaics through the preservation of primary agricultural use. In Ukraine, similar criteria are still needed for minimum agricultural productivity, acceptable land occupation by structures, monitoring of crop yield, safety requirements, and compatibility with land-use planning. Without such standards, spatial models can support discussion, but they cannot fully define implementation rules.

Mapped power lines and substations do not provide grid capacity, connection feasibility, voltage, ownership, or infrastructure condition. Open water and building layers require local verification. The current model does not include Sentinel-2 vegetation indices, DEM-derived slope and aspect, parcel-level legal status, crop rotation, soil productivity, microrelief, or engineering-grade topographic accuracy. Therefore, the map should be understood as an initial screening product for planning discussions, not as a project-ready site selection.

Conclusions

An important methodological outcome of this study is the distinction between a suitability map and an implementation-ready planning document. The proposed AI-GIS workflow can quickly identify areas where agrivoltaic development may be reasonable for further investigation. However, the resulting map should not be interpreted as a direct recommendation for construction. It is a preliminary spatial screening product that helps to reduce the search area, structure the discussion between planners and engineers, and define where additional field data are most needed.

The obtained results also demonstrate the value of transparent open-data modelling for Ukrainian communities. In post-war recovery conditions, local authorities may need rapid spatial evidence before detailed engineering surveys become available. Open administrative boundaries, OpenStreetMap layers, GIS-MCDA procedures, and Random Forest classification can provide a first approximation of spatial opportunities. This is especially useful for comparing alternative territories and identifying zones where agricultural use, road accessibility, and proximity to mapped power infrastructure are combined in a favourable way.

At the same time, the study shows that open data cannot fully replace authoritative datasets. The most important limitation is the lack of detailed information about the actual capacity and technical condition of the electricity grid. A mapped power line or substation does not mean that connection is technically or economically possible. Therefore, future agrivoltaic planning should combine GIS screening with data from distribution system operators, local energy plans, and technical connection assessments.

Another limitation is related to agricultural and cadastral information. Agrivoltaics requires not only suitable land cover, but also compatibility with crop production, machinery movement, land ownership, land-use designation, soil quality, and long-term agricultural productivity. These aspects cannot be reliably evaluated only from open vector layers. For this reason, the proposed model should be followed by parcel-level cadastral analysis, soil assessment, consultation with agricultural producers, and field validation.

Geodetic accuracy is also essential for moving from screening to project design. In this study, coordinate harmonization was sufficient for preliminary distance and area calculations. However, engineering design of agrivoltaic systems requires much more precise information about terrain, slopes, drainage, access roads, and construction constraints. Future work should therefore include high-resolution topographic data, UAV or GNSS-based survey, and careful control of horizontal and vertical reference systems. This is particularly important in the context of Ukraine's transition to European geodetic and height reference frameworks.

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