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# A GIS-Based Approach to Identifying Suitable Areas for Positive Energy Districts Development †

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**Abstract**

Positive Energy Districts (PEDs) have been proposed as a holistic approach to urban decarbonization. PEDs are defined as delimited areas that produce, annually, more energy than they consume. The methodology proposed for PED assessment integrates multicriteria decision-making geospatial analysis and weighted overlay techniques to assess PED suitability across different dimensions. Data harmonization is included as part of the modeling process, ensuring methodological consistency across diverse contexts. The approach employs a layer overlay and aggregation through a weighting average process, calibrated through stakeholder input, to reflect local priorities and urban-specific conditions in order to identify the potential areas for PED implementation. Geospatial datasets provided as inputs are processed to produce maps that reflect the PED suitability index for the city districts according to the selected dimensions. As a result, the open-source developed MCDA algorithm provides maps that facilitate the identification of relevant zones for PED feasibility. The algorithm was applied in Bratislava city, understanding its identification potential, adaptability and scalability to other cities. The obtained results highlight the most interesting districts in which to build a PED in Bratislava, promoting the algorithm as a replicable decision-making tool for advancing PED identification and deployment.

**Keywords:** Positive Energy Districts; Multi-Criteria Decision Analysis; Geographical Information Systems; district dssessment; energy; feasibility

## 1. Introduction

The transition towards sustainable urban development requires a shift from centralized, fossil-fuel-based energy systems to decentralized, renewable-driven models. Cities are responsible for over 70% of global energy consumption and $CO_2$ emissions [1], requiring the adoption of innovative solutions to meet ambitious climate targets. In this context, Positive Energy Districts (PEDs) emerge as a key strategy, aiming to create urban areas that generate more renewable energy than they consume. PEDs represent a fundamental shift in urban energy planning, integrating high-efficiency buildings, smart grids, renewable energy production, and flexible energy management within a selected district [2,3]. Building on earlier concepts such as nearly/net zero energy buildings and energy-positive neighborhoods [3,4], PEDs extend the focus from single buildings to the

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district scale to better exploit synergies between diverse building typologies, infrastructures and urban functions [4,5].

PEDs are defined as energy-efficient and energy-flexible urban areas or groups of connected buildings that produce net zero greenhouse gas emissions and actively manage an annual local or regional surplus of renewable energy, requiring the integration of multiple systems and infrastructures while ensuring "a good life for all" in line with social, economic and environmental sustainability [2,6]. PEDs should therefore be understood as one component within a broader urban decarbonization portfolio, rather than a stand-alone solution for the full emissions and energy footprint associated with urban areas. In this sense, PEDs remain valuable as a practical, district-scale pathway to accelerate the integration of efficiency, local renewables, flexibility and smart energy management, while providing replicable planning and decision-support approaches that cities can scale and combine with wider mitigation measures. However, the PED concept remains heterogeneous in practice, where multiple and partially overlapping definitions coexist, differing in system boundaries, energy balance metrics and the treatment of off-site resources [4,5,7]. This lack of consensus complicates the operationalization and comparison of PEDs and poses challenges for the development of robust assessment frameworks and design tools.

At the same time, PEDs are increasingly recognized as complex socio-technical systems embedded in wider urban and regional contexts, where technological, institutional and social dimensions co-evolve. The work in [4] conceptualizes PEDs as complex adaptive systems linked to resilience and broader sustainability frameworks, while ref. [6] identifies interdependent challenges and rank governance, social factors, market conditions and technical issues as critical success factors for PED implementation. Previous research on Positive Energy Districts and sustainable plus-energy neighborhoods shows that PED planning and design are highly context-dependent, requiring early and explicit energy ambitions, strong collaboration between stakeholders, and adaptation of measures to local institutional and energy system conditions [8]. Stakeholder engagement and cross-sectoral collaboration are essential to ensure that PEDs deliver not only energy and emissions benefits, but also social acceptance and co-created solutions [5,6].

Different methodological approaches have been proposed to support the design and assessment of PEDs. The research in [9] presents a calculation methodology to achieve PEDs in cities, while ref. [7] compares several energetic assessment methodologies and shows that requiring a strictly positive annual energy balance can be a demanding prerequisite that excludes many urban districts with limited local renewable potential. They argue instead for more holistic assessment schemes that combine quantitative energy indicators (e.g., energy balance, flexibility, self-sufficiency) with environmental, economic and social key performance indicators [7]. At a process level, ref. [10] reviews existing PED design methodologies and introduces PlanPED framework that structures the planning, design and implementation of PEDs, addressing the lack of energy planning culture and adequately skilled staff in many cities while emphasizing the need for practical, stepwise tools for municipalities.

Methodologies typically in the PED definition include technology feasibility [3], evaluation of energy balances and system configurations [7,9], or development of decision-making tools and structured design workflows [5,8,10]. It is important to highlight the role of Geographical Information Systems (GISs) in the evaluation of the urban context, where high-resolution geolocated data has a significant impact on providing accurate results for decision-making processes. GIS-based methodologies have been widely used in renewable energy potential assessments and in multi-criteria spatial analyses for energy planning, such as PV (photovoltaic) site selection [11,12], micro-hydropower suitability [13,14] and wind farm location studies [15,16]. In most of these studies, high-

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resolution spatial data have been crucial for accurate analysis, especially for technical criteria such as solar irradiation, terrain, land use and proximity to infrastructure [11–16]. By contrast, socio-economic data are often less readily available or up-to-date in some regions [16], and several studies emphasize the importance of freely available data sources, which are particularly beneficial in regions with limited analytical resources [11,15].

Advances in geospatial artificial intelligence and data-intensive geospatial analytics provide a clear opportunity to extend GIS–MCDA suitability workflows beyond static, map-based screening. Combining GIS with AI/ML and MCDA can strengthen urban planning decision support by adding data-driven insights and predictive layers to expert-based multicriteria evaluation [17]. At the same time, the rapid growth of geospatial data from remote sensing and IoT sensors creates opportunities to update key spatial indicators at higher temporal resolution, improve local context representation and enable near-real-time suitability monitoring and more dynamic PED boundary delineation that requires scalable data processing and integration [18].

Although GIS-based studies provide valuable insights for renewable energy planning, they are not specifically tailored to the identification and delineation of PEDs. In the framework of the EU project MAKING-CITY, ref. [19] proposes a flexible GIS-MCDA methodology to identify suitable PED areas, considering resource availability (solar, wind, geothermal, water, biomass and waste heat), urban macro-form, land-use context, virtual and physical energy infrastructures, and socio-economic and socio-cultural aspects. Their work demonstrates the potential of GIS-Multi-Criteria Decision Analysis (MCDA) to support the early stages of PED planning and to inform district selection at city level. However, the suggested approach could have limitations related to data availability, requiring harmonized layers to be covered with datasets from public sources.

Overall, existing PED research reveals several interrelated gaps. First, there is a lack of standardized, transparent and replicable spatial methodologies for systematically screening urban areas to identify those with the highest potential for PED development, using criteria that are both conceptually grounded and operational in practice [4,5,7,10,19]. Second, despite increased attention to replication and upscaling in different projects, methods for PED site selection are rarely designed from the outset to be transferable across different cities with heterogeneous data conditions [8,10,19]. Third, although MCDA is widely used in GIS-based energy planning, the sensitivity of spatial suitability results to the choice of weighting schemes, which is relevant in participatory decision-making with multiple stakeholders, has received limited explicit attention in the PED literature.

The successful deployment of PEDs requires accurate, transparent and replicable methodologies for site selection that can be seamlessly integrated with existing urban infrastructure. To address these challenges, this study develops a GIS-based spatial assessment framework that enables urban planners to identify optimal locations for PEDs, explicitly designed with replication in mind thanks to the integration of variables that could be fitted with public datasets. The research is guided by two main questions: how GIS-based methodologies can be used to optimize the spatial identification of suitable areas for PEDs, and which factors influence the replicability of PED planning approaches in diverse urban environments. To answer them, the proposed analytical framework integrates energy-related, socio-economic and land-use datasets for PED site selection, and establishes a replicability assessment model that defines key parameters for adapting PED concepts across cities. By pursuing these objectives through a GIS-based MCDA, the study aims to provide a decision-support framework for policymakers and urban planners, enhancing spatial planning and policy development at the municipal level, facilitating PED deployment, regulatory alignment, and ultimately contributing to the broader urban sustainability agenda with practical tools and strategies for identifying and implementing PEDs.

## 2. Materials and Methods

This study demonstrates a GIS-based decision-support methodology developed to evaluate urban areas or municipalities, identifying districts with higher potential to evolve into Positive Energy Districts (PEDs). The proposed method is built to cover a structured workflow that requires the provision of the following steps: (i) definition of city needs and priorities, (ii) collection and preparation of spatial/non-spatial datasets, (iii) creation and normalization of GIS layers, (iv) weighting and overlay analysis, (v) generation of suitability maps under alternative weighting scenarios, and (vi) validation/approval of scenarios with local stakeholders through co-creation activities to select the most promising areas for further PED detailed design. These steps are represented in Figure 1 and connected with the MCDA algorithm workflow.

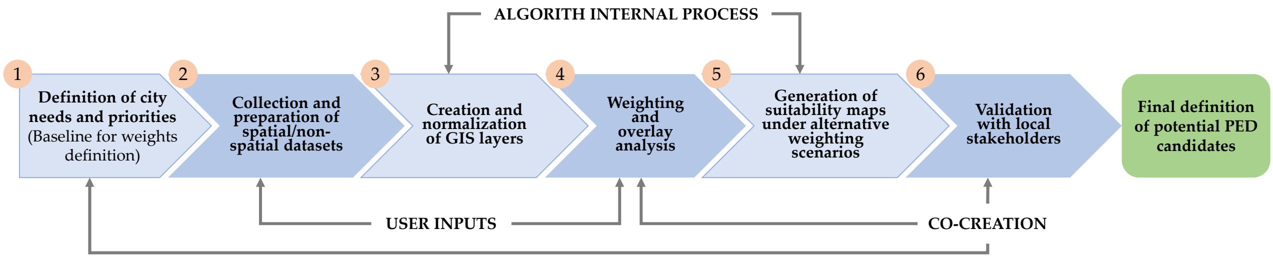


**Figure 1.** Potential PED identification workflow. The arrows connect the steps where user input, co-creation, and the algorithm is requested.

The assessment is organized around five PED-related dimensions selected via thorough literature review: efficient buildings, net zero energy imports, energy flexibility, affordability, and livability. Each dimension needs to be represented by one or more spatial layers in the MCDA implementation to reduce bias and ensure balanced coverage of technical, socio-economic and urban-form drivers in PED identification. It should be noted that the layers used in the identification of potential PED areas represent the current dynamics of each variable, such as, for example, current energy demand, but do not consider their dynamic evolution in the future. The complete workflow is implemented in Python 3.12, and requires city-specific datasets and expert knowledge to define weights and validate the results, improving both automation in obtaining results and the transferability of the methodology to other areas.

### 2.1. Multi-Criteria Decision Analysis Methodology

The required activities in the GIS-based Multi-Criteria Decision Analysis (MCDA) are presented in Figure 2 and used to compute a composite PED suitability index through four conceptual steps: (i) definition of PED dimensions and variables, (ii) normalization and suitability assessment of the corresponding GIS layers, and (iii) weighting and overlay aggregation to (iv) produce the final index making feasible scenario comparison. These four conceptual steps are defined below:

- **Geospatial database construction:** The first step is the definition of relevant variables to identify a PED. Once variables are selected and grouped to configure the dimensions, each variable is represented as a spatial vector GIS layer (GeoJSON format). When inputs are tabular (e.g., district socio-economic statistics), attributes are joined to spatial geometries (districts/parcels/buildings) to create the vector layer, enabling subsequent spatial analyses.
- **Normalization and suitability classification:** To make heterogeneous indicators comparable, each GIS layer is rasterized and normalized onto a common five-class suitability scale (0–100). Normalization is percentile-based (i.e., adapted to each layer's

distribution), ensuring comparability even when absolute values differ between cities and/or districts. This makes it easier to combine indicators in a composite index for the MCDA process, avoiding the effect of outliers in the analysis by generating homogeneous classes for comparison purposes. The final suitability classes defined per layer are: 0 (not suitable), 25 (least suitable), 50 (moderate suitable), 75 (highly suitable), 100 (most suitable).

- **Weighting and aggregation:** Normalized raster layers are combined using weighted averages to compute dimension-level rasters, which are then normalized again and aggregated (weighted average) into the final PED suitability index.
- **Scenario implementation:** A baseline scenario using equal weights for layers and dimensions is produced, comparable with city-specific scenarios that are produced by adjusting weights through stakeholder consultations, enabling exploration of trade-offs and local priorities.

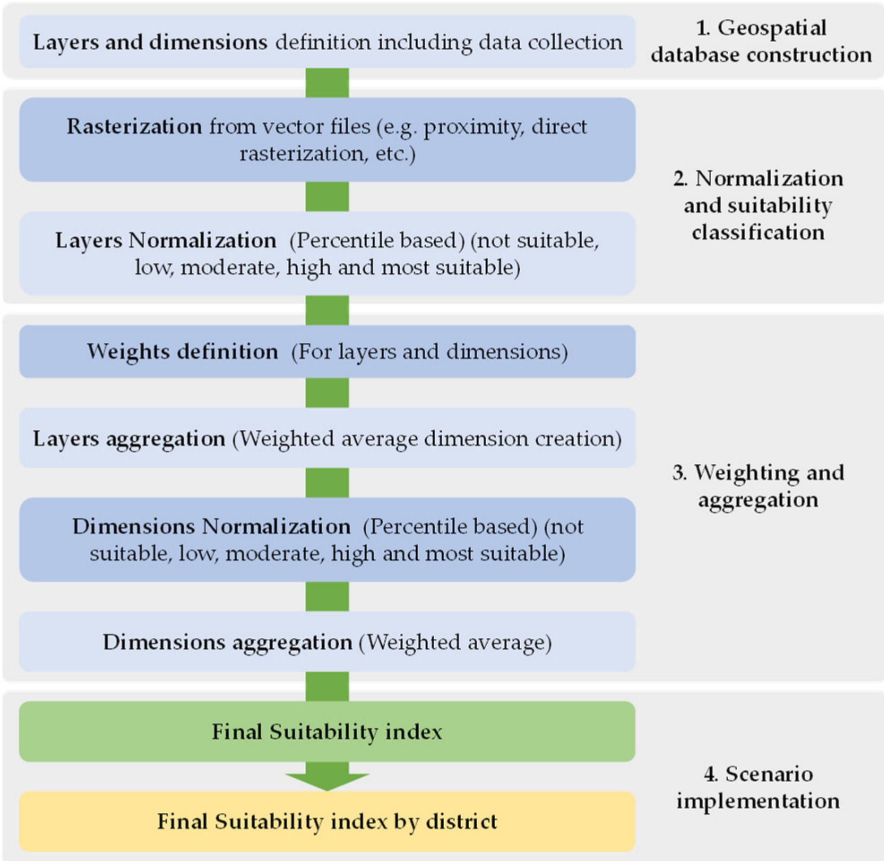


**Figure 2.** Overview of the data processing workflow included in the Multi-Criteria Decision Analysis algorithm. The arrow represents that all processes are sequential and linked together.

### *2.2. Data Collection for Layers Development*

The development of the GIS layers used in the MCDA framework required the systematic collection of heterogeneous datasets, combining city-provided information and open datasets from EU services like CORINE Land Cover from the Copernicus Land Monitoring Service (CLMS) [20]. The selection of data to create the layers follows the definition of five PED dimensions (efficient buildings, net zero energy imports, energy flexibility, affordability, and livability), where each dimension is represented by a set of geolocated variables. Data requirements were structured according to the layer inventory presented in Table 1, which links each dimension/subdimension to the target layer or layers and the specific datasets needed to generate them.

**Table 1.** Requested datasets to create each layer and PED dimension.

| Dimension | Subdimension | Layer and Description | Requested Data |
|---|---|---|---|
| Efficient buildings | Building stock characterization | Heating energy demand per $m^2$ ▪ Cooling energy demand per $m^2$ ▪ DHW energy demand per $m^2$ ▪ Electrical energy demand per $m^2$ | Building typology, use and occupancy patterns ▪ Buildings geometries |
| Net zero energy imports | RES potential | Solar energy potential ▪ Wind energy potential ▪ Geothermal potential ▪ Biomass potential | LiDAR data ▪ DTM and DSM ▪ Buildings geometries ▪ PVGIS data [21] |
| Energy flexibility | Alternative energy resources | Industrial area (heat) ▪ Water bodies (heating and cooling) ▪ Forest areas (biomass) | Urban Atlas Land Cover [22] ▪ CORINE Land Cover [20] |
| Affordability | Economic context | Share of energy expenditure in income ▪ Investment plan existence | District values on income level ▪ City statistical data |
| Livability | Social cohesion | Aging rate ▪ Per capita income level ▪ Ownership of the property ▪ Employment rate per district ▪ Vulnerability ▪ Population density/change | District values on income level and property ▪ City statistical data ▪ The Humanitarian Data Exchange [23] |
| | Urban complexity | Residential and other land uses balance ▪ Location of green areas ▪ Building density | Urban Atlas ▪ Corine Land Cover ▪ OSM buildings ▪ Cadaster |

Once collected, in some cases, datasets need to be prepared to ensure consistency with the requirements of the MCDA processing algorithm. In this sense, a common data model was adopted where input layers are delivered as vector files (GeoJSON format) with harmonized attributes. Several layers require dedicated algorithms (e.g., demand modeling, Renewable Energy Sources (RESs) potential computation) to obtain the inputs required in the MCDA algorithm.

#### 2.2.1. Efficient Buildings

The efficient buildings dimension represents building energy needs that were estimated using data from the building stock characteristics (building use, height, year of construction and occupancy patters), creating four intensity layers calculated in kWh/$m^2$: heating, cooling, domestic hot water (DHW) and electricity demand. Demand was estimated through equations following the methodological framework provided by the Energy Performance of Buildings Directive (EPBD) [24]. Required inputs include building typology, use and occupancy patterns, as well as building geometries. Outputs are provided as vector layers (GeoJSON format) for each building energy demand component. Higher energy demand represents areas with greater potential for a PED implementation due to their decarbonization potential.

#### 2.2.2. Net Zero Energy Imports

The net zero energy imports dimension evaluates the potential for local renewable generation to reduce external energy dependence by integrating solar (rooftop and land), wind (rooftop and land), geothermal and biomass resources. Computation uses CARTIF-developed algorithms within the RENERMap project (Dynamic map of renewable potential at municipality scale) [25], requiring LiDAR data or DTM/DSM models, building and parcels boundaries, Leaf Area Index (LAI) values, fraction of covered area in forest land and solar radiation and wind velocities from PVGIS. Constraint layers (e.g., roads, railways, forest/protected areas, power lines) are used to exclude non-available land for energy generation. Outputs are multiple GeoJSON layers including rooftop/land solar potential (by PV technology), wind (rooftop and land by technology) potential, and geothermal and biomass potentials, all of them measured in kWh/$m^2$. In this case, areas with higher renewable energy potential are more suitable as candidates for the implementation of a PED, as they can produce the energy requested to cover the demand with renewables.

The estimation of renewable energy potential is based on a set of geospatial algorithms designed to work at both the building and land-parcel scale. These algorithms integrate high-resolution spatial data, climate data and environmental constraints to characterize exploitable areas for RES implementation and those with limitations or that are unsuitable. In the case of solar resources, the methods differ between rooftop and ground-mounted installations and consider different photovoltaic technologies (crystalline silicon (crys), and amorphous silicon (amf)), while also considering geometric factors such as orientation and slope, shading effects and regulatory restrictions. Wind potential is assessed for rooftop and ground-mounted installations, considering both vertical and horizontal axis technologies and their specific performance and constraints related to location and available resources. Geothermal potential is assessed based on the thermal properties of shallow soil and the available installation area close to the consumption spaces, while biomass potential is derived from sustainable forest growth as a limiting factor and vegetation structure.

#### 2.2.3. Energy Flexibility

The energy flexibility dimension represents the district's capacity to integrate alternative or flexible energy resources. It could be determined by analyzing proximity to: (i) industrial heat sources, (ii) water bodies for heating and cooling, and (iii) biomass resources (forest areas). Urban Atlas and Corine Land Cover are used to select the areas covered by the required land used. The outputs are GeoJSON polygon layers representing industrial areas, water bodies and forest areas, used subsequently for the development of proximity metrics in the MCDA algorithm. To understand the effect of these variables in PED identification, it should be noted that areas closer to renewable energy resources are more attractive for the deployment of PEDs.

#### 2.2.4. Affordability

The affordability dimension transforms socio-economic factors into quantitative values suitable for comparison and overlay. It includes indicators such as the share of energy expenditure in income and the existence of investment plans (with brownfield location and distance as an optional proxy). Data collection relies on local data collected at city level. In order to create an affordability index as a dimension in the MCDA algorithm, the vector layers that represent the district energy-expenditure and brownfield locations are required as inputs. For the affordability dimension, areas with higher economic resources and ongoing investment plans have more interest as candidates for the implementation of a PED.

#### 2.2.5. Livability

This dimension is divided into two subdimensions that worked as two specific dimensions in the MCDA process: social cohesion and urban complexity. The social cohesion subdimension captures community vulnerability and resilience using indicators like aging rate, per capita income, property ownership, employment rate, a composite vulnerability index, and population density or specific change. Inputs are collected through questionnaires at city level and local statistics collected at district level, being complemented with external population-density sources (Humanitarian Data Exchange). Outputs are produced as district-level GeoJSON layers suitable for rasterization and integration into the MCDA. The urban complexity subdimension evaluates urban form and livability through: (i) green space accessibility (including forest), (ii) mixed-use patterns (calculated using the Shannon index), and (iii) building density, plus the balance between residential and other land uses. Data sources include Urban Atlas, Corine Land Cover and complementary datasets such as OSM (OpenStreetMap) [26] building and cadaster. Outputs are GeoJSON layers representing buildings, green spaces and land-use polygons, enabling derivation of density/proximity and mixed-use metrics. Vulnerable areas (low income, aged or low employment rate) need to be prioritized for a PED deployment, while urban ecosystems with high building density, low urban spaces and land diversification are also functional areas for the development of a PED. From an energy-justice perspective, these vulnerable districts are more exposed to energy poverty, having lower adaptive capacity to energy price volatility and climate stressors, so PED measures can yield disproportionate social benefits like lower bills or improved comfort. On the other hand, dense and space-constrained urban areas concentrate demands facilitating collective solutions as shared generation or storage, improving techno-economic feasibility.

### *2.3. Implementation of the Python-Based MCDA Framework*

The complete GIS–MCDA workflow (Figure 3) has been implemented and automated in Python 3.12 as a modular and scalable pipeline, designed for replication across cities with minimal adaptation (mainly the definition of weights). The implementation relies on open-source libraries, primarily *GeoPandas* for vector processing and *Rasterio* for raster operations, and is structured into: (i) configuration and data ingestion, (ii) spatial harmonization/geoprocessing, (iii) normalization, weighting and suitability characterization, and (iv) output generation.

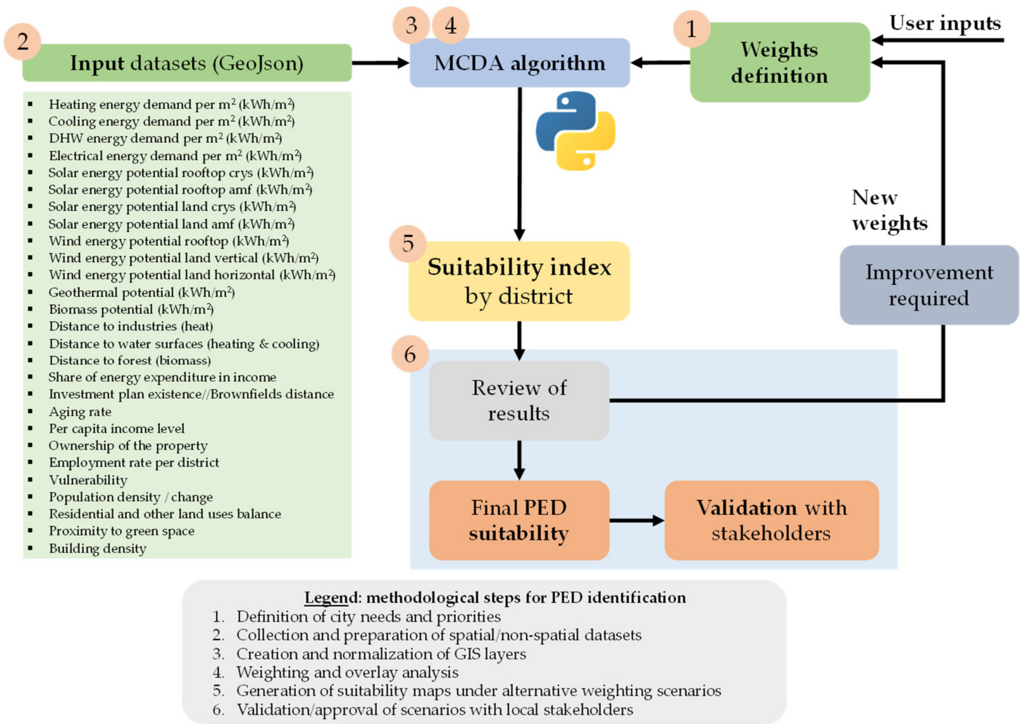


**Figure 3.** MCDA algorithm linkages, including the inputs for the suitability index calculation. The arrows provide information about the flow of information in the execution of the algorithm.

To ensure comparability across layers, a common data model is applied in the Python pipeline. Input layers are provided as GeoJSON files, and all data are reprojected to a common CRS (ETRS89-extended/LAEA Europe, EPSG:3035), clipped to municipal boundaries, and rasterized to a shared spatial resolution (5 m). A resolution of 5 m is selected to ensure accurate differentiation of areas within the urban environment, as each pixel represents an area of 25 $m^2$. For the economic indicators (created at district level), the resolution is maintained to guarantee comparability, even though there is no differentiation in pixel values between districts. The pipeline performs reprojection, clipping, rasterization/resampling, proximity analysis (where needed), percentile-based reclassification to the 0–100 suitability scale, and weighted overlay aggregation to produce the final PED suitability index and scenario maps as raster files in GeoTIFF format.

## 3. Case Study and Scenario Definition

The proposed GIS–MCDA framework has been applied in Bratislava through the Py-thon algorithm in order to validate it into a real urban context. Thus, the objective is twofold: first, to demonstrate the operationalization of the methodology under real data availability and policy constraints; and second, to assess how locally defined priorities influence the spatial identification of areas with high potential for Positive Energy District (PED) development.

Bratislava was selected as a representative medium-sized European capital facing typical challenges associated with historic urban fabric, energy-intensive building stock, and limited municipal fiscal autonomy. The case study is part of the ATELIER project, whose objectives involve the development of a city-specific replication plan, the application of the GIS-MCDA tool for potential PED areas selection, and a structured co-creation process with local stakeholders for PED design in the selected areas.

### *3.1. Bratislava Case Study Context*

Bratislava is the capital and largest city of the Slovak Republic and represents a compact metropolitan area characterized by a heterogeneous building stock, a strong presence of heritage-protected zones, and a high reliance on centralized energy systems. These features make the city a particularly relevant case for testing spatial decision-support tools aimed at identifying feasible locations for PEDs.

From a strategic perspective, Bratislava has committed to ambitious climate and energy objectives through its long-term development strategy Bratislava 2030 [27], which prioritizes energy efficiency, renewable energy deployment, sustainable mobility and climate resilience. Such a strategic plan has defined the city's development plan since its approval in June 2022. The city is also part of the European Mission for Climate-Neutral and Smart Cities [28], targeting climate neutrality by 2030. This policy alignment provides a favorable framework for PED experimentation, while simultaneously imposing stringent requirements on feasibility, scalability and social acceptance.

Bratislava faces several structural limitations that directly affect PED implementation. The city operates within a highly centralized fiscal system, with limited financial autonomy and strong dependence on national redistribution mechanisms. This constrains the capacity for large-scale public investment and increases reliance on European funding programs. Additionally, a significant share of the building stock consists of post-war residential blocks and historically protected buildings, which pose technical and regulatory challenges for deep energy retrofitting and on-site renewable energy integration.

From an energy system perspective, Bratislava is characterized by an extensive district heating network that plays a central role in urban energy supply. Ongoing decarbonization efforts include the integration of waste-to-energy, wastewater heat recovery and future renewable heat sources. This makes the city an interesting testing ground for PED concepts that rely not only on building-level interventions but also on district-scale energy infrastructure and sector coupling.

### *3.2. Weighting Schemes and Scenario Design*

To test the approach, a baseline scenario was first generated using equal weights across all layers inside the dimension and within-dimensions. Equal weights have been considered for the variables within the dimension and between dimensions to establish a baseline scenario avoiding the introduction of subjective or arbitrary biases by the analyst, In this sense, equal weights produce a control scenario (baseline) that can be used to evaluate by small changes the sensitivity of each variable and dimension in the PED identification process. A second scenario was then produced using revised, city-specific weights reflecting Bratislava's priorities (e.g., higher emphasis on energy demand and rooftop crystalline PV and geothermal potential). The weights of the layers in each of the scenarios are presented in Table 2 while the weights of each dimension per scenario are defined in Table 3. The results could provide a comparative spatial analysis of suitability for PED implementation under both scenarios, showing how alternative weighting strategies modify the spatial distribution of least-to-most suitable areas for PED development.

**Table 2.** Weights per layer given by Bratislava stakeholders and equal weights assignment * (crys: crystalline silicon; amf: amorphous silicon).

| Dimension and Subdimension | Layers | Weight of Each Layer (%): Equal | Weight of Each Layer (%): Experts |
|---|---|---|---|
| Efficient buildings | Heating energy demand per m$^2$ (kWh/m$^2$) | 25 | 20 |
| | Cooling energy demand per m$^2$ (kWh/m$^2$) | 25 | 25 |
| | DHW energy demand per m$^2$ (kWh/m$^2$) | 25 | 30 |
| | Electrical energy demand per m$^2$ (kWh/m$^2$) | 25 | 25 |
| Net zero energy imports | Solar energy potential rooftop crys (kWh/m$^2$) * | 11.11 | 40 |
| | Solar energy potential rooftop amf (kWh/m$^2$) * | 11.11 | 0 |
| | Solar energy potential land crys (kWh/m$^2$) * | 11.11 | 0 |
| | Solar energy potential land amf (kWh/m$^2$) * | 11.11 | 0 |
| | Wind energy potential rooftop (kWh/m$^2$) | 11.11 | 5 |
| | Wind energy potential land vertical axis(kWh/m$^2$) | 11.11 | 5 |
| | Wind energy potential land horizontal axis (kWh/m$^2$) | 11.11 | 0 |
| | Geothermal potential (kWh/m$^2$) | 11.11 | 40 |
| | Biomass potential (kWh/m$^2$) | 11.11 | 10 |
| Energy flexibility | Distance to industries (heat) | 33.34 | 60 |
| | Distance to water surfaces (heating and cooling) | 33.33 | 20 |
| | Distance to forest (biomass) | 33.33 | 20 |
| Affordability | Share of energy expenditure in income | 50 | 30 |
| | Investment plan existence//Brownfields distance | 50 | 70 |
| Livability (Social cohesion) | Aging rate | 16.66 | 0 |
| | Per capita income level | 16.67 | 15 |
| | Ownership of the property | 16.67 | 40 |
| | Employment rate per district | 16.66 | 15 |
| | Vulnerability | 16.67 | 15 |
| | Population density/change | 16.67 | 15 |
| Livability (Urban complexity) | Residential and other land uses balance | 33.34 | 30 |
| | Proximity to green space | 33.33 | 50 |
| | Building density | 33.33 | 20 |

As was previous explained, the equal-weight configuration was used as a neutral reference to avoid introducing biases and to ensure that all PED dimensions contribute uniformly to the composite index. Following this initial run, the baseline maps and district-level indicators were discussed with Bratislava stakeholders through a structured co-creation activity, defined as a participatory process in which local actors jointly (i) review suitability outputs, (ii) assess their relevance and implications, and (iii) agree on context-specific refinements in the weight to improve the results. Co-creation was selected as the validation approach due to PED targeting, being inherently context-dependent as it combines technical constraints (urban form, distance to resources) with normative and strategic considerations (social vulnerability or income). Considering this, validation requires not only internal consistency checks but also external experts' validity to be covered by actors with local knowledge and implementation responsibilities. Participants were included using purposive sampling to ensure representation of the key roles involved in PED planning and delivery. Five stakeholders representing policymakers, energy experts and governance actors were involved in the validation process. The co-creation step followed a replicable protocol with: (a) a short briefing on objectives and on the baseline outputs; (b) guided review of maps and indicators to identify mismatches with local conditions; (c) definition of priorities and constraints; and (d) consensus on adjustments to the weighting scheme. Specifically, the weighting scheme was revised to reflect local strategic priorities and perceived feasibility constraints identified during the session, with changes documented and incorporated into the subsequent model run. In practice, weights were adjusted to capture both technological emphasis (e.g., prioritizing rooftop PV and geothermal resources over other RES options) and planning focus (e.g., assigning higher relevance to energy demand reduction). The weightings of the indicators were agreed upon and established through a consensus among the stakeholders involved in the co-creation process for their definition, after an initial presentation of the methodology and the results obtained for the baseline or control scenario.

**Table 3.** Weights per dimension given by Bratislava stakeholders and equal weights assignment.

| Dimension and Subdimension | Weight of Each Layer (%): Equal | Weight of Each Layer (%): Experts |
|---|---|---|
| Efficient buildings | 16.67 | 35 |
| Net zero energy imports | 16.67 | 25 |
| Energy flexibility | 16.67 | 8 |
| Affordability | 16.67 | 7 |
| Livability (Social cohesion) | 16.66 | 10 |
| Livability (Urban complexity) | 16.66 | 15 |

## 4. Results

The results for the city of Bratislava are presented as a comparative assessment between the equal-weights baseline scenario and the city-specific weighting scenario (Figure 4). This side-by-side representation allows for a direct evaluation of how stakeholder-defined priorities influence the final spatial pattern of PED suitability. As shown in Figure 4, the two scenarios lead to clearly different suitability distributions, represented by scales and colors, where reds represent the most interesting areas or candidates for PED implementation and greens the opposite. While the equal-weights approach produces a more balanced contribution of all thematic layer groups, the city-weight configuration amplifies the influence of the dimensions prioritized by Bratislava stakeholders. Consequently, several areas change their suitability class (from least/moderately suitable to highly/most suitable, or vice versa), resulting in different values of the suitability index and different maps of results, even though some high-performing districts remain consistently prominent for PED implementation across both scenarios.

To support interpretation at the neighborhood scale, Figure 4 also includes zoomed-in views of selected locations. These detailed panels illustrate how the weighting strategy affects the spatial continuity, fragmentation, and concentration of suitable zones within districts, highlighting local hotspots that may be overlooked on a city-wide scale. The results confirm that the weighting step is not merely a numerical adjustment. It is the most decisive factor shaping the identification of priority areas for PED development in an urban area like the Bratislava municipality.

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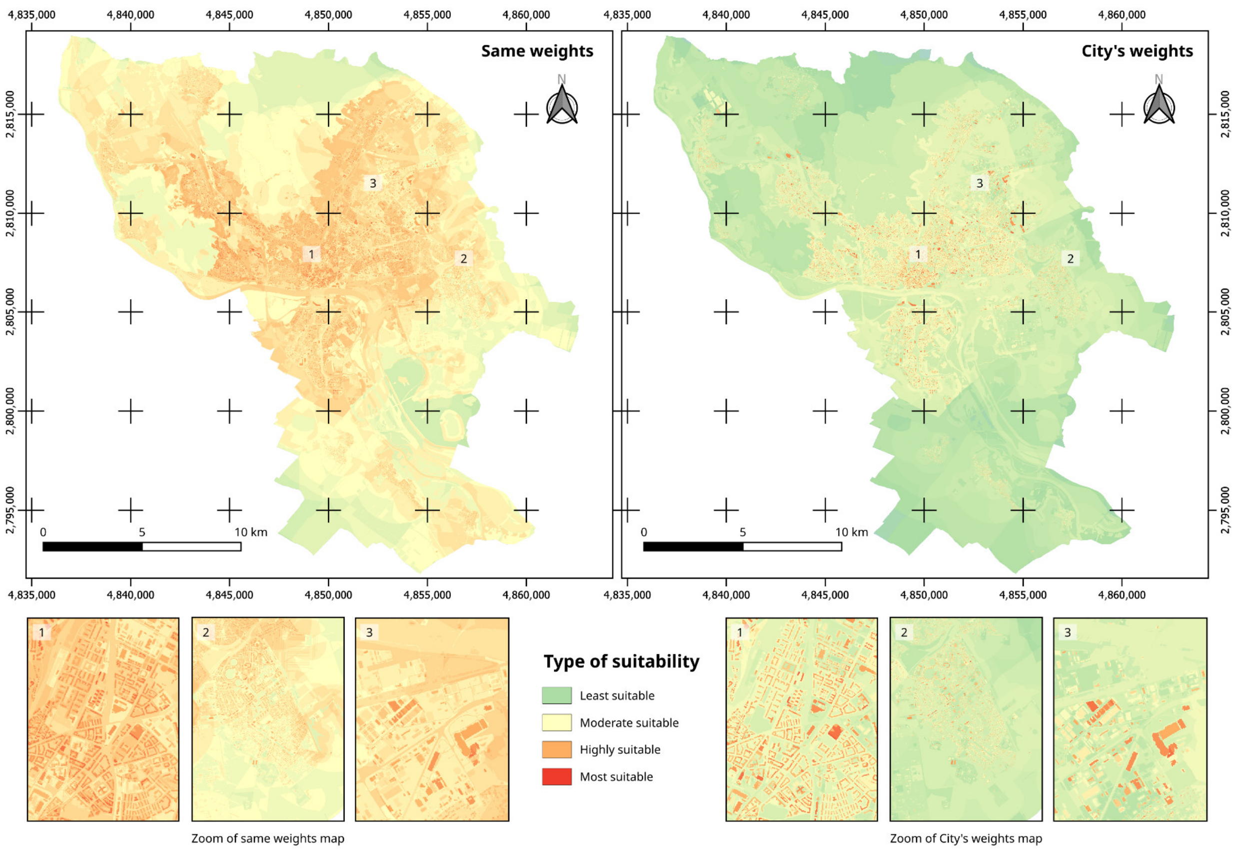


**Figure 4.** Map of the results for Bratislava (right part with equally distributed weights for each group of layers; left part with city's weights: giving more prioritization to the energy demand layer). Numbers 1, 2 and 3, represent areas of the municipality with a higher zoom level.

The Bratislava case study was analyzed under two weighting schemes: a baseline scenario with equal weights across dimensions and layers, and a second scenario using city-specific weights reflecting Bratislava's stakeholders' priorities. Under equal weights, the district suitability index ranges from 47.33 to 64.84, with an overall average of 55.10. The highest-scoring districts are Staré Mesto (64.84), Karlova Ves (62.87), Dúbravka (61.89), Lamač (60.60) and Petržalka (58.94), indicating a concentration of suitability in central and inner-city areas (Table 4).

When applying city weights, the suitability range becomes 29.30 to 48.99 (mean 37.16), while the leading districts remain Staré Mesto (48.99) and Karlova Ves (43.34). In this scenario, Petržalka (42.68) and Ružinov (42.48) move up in the ranking, followed closely by Dúbravka (42.11) and Nové Mesto (40.54). Overall rankings are broadly consistent between scenarios, but relevant shifts are visible: Podunajské Biskupice shows the largest improvement (from 17th to 9th, reaching 35.18), while Lamač (from 4th to 7th), Čunovo (from 12th to 15th) and Záhorská Bystrica (from 14th to 17th) are the districts that fall the most in the ranking. These differences confirm that the city-weight configuration modifies the spatial prioritization of districts, likely favoring areas that better match Bratislava's emphasis on energy demand and selected local RES options (e.g., rooftop PV and geothermal), while still keeping core districts among the most suitable candidates for a potential PED implementation.

Figure 5 outlines in purple the location of the two districts with the highest potential for developing a PED, according to the results obtained from applying the MCDA algorithm. It should be noted that these two districts are characterized by a high building density; therefore, they demand large amounts of energy but also have significant rooftop potential for deploying renewable energy generation solutions. It should be noted that this statement is corroborated by the reddest areas in the figure, which are where a high building density predominates.

**Table 4.** Mean values results of the application of the different weights.

| District | Mean Value with Equal Weights | Mean Value with City Weights |
|---|---|---|
| Devínska Nová Ves | 54.00 | 35.07 |
| Záhorská Bystrica | 49.91 | 29.30 |
| Devín | 49.95 | 32.05 |
| Dúbravka | 61.89 | 42.11 |
| Lamač | 60.60 | 38.77 |
| Nové Mesto | 57.39 | 40.54 |
| Rača | 53.22 | 38.67 |
| Vajnory | 52.77 | 34.93 |
| Karlova Ves | 62.87 | 43.34 |
| Staré Mesto | 64.84 | 48.99 |
| Ružinov | 58.48 | 42.48 |
| Vrakuňa | 55.28 | 35.16 |
| Petržalka | 58.94 | 42.68 |
| Podunajské Biskupice | 47.33 | 35.18 |
| Jarovce | 48.67 | 29.57 |
| Rusovce | 48.06 | 31.75 |
| Čunovo | 52.56 | 31.12 |

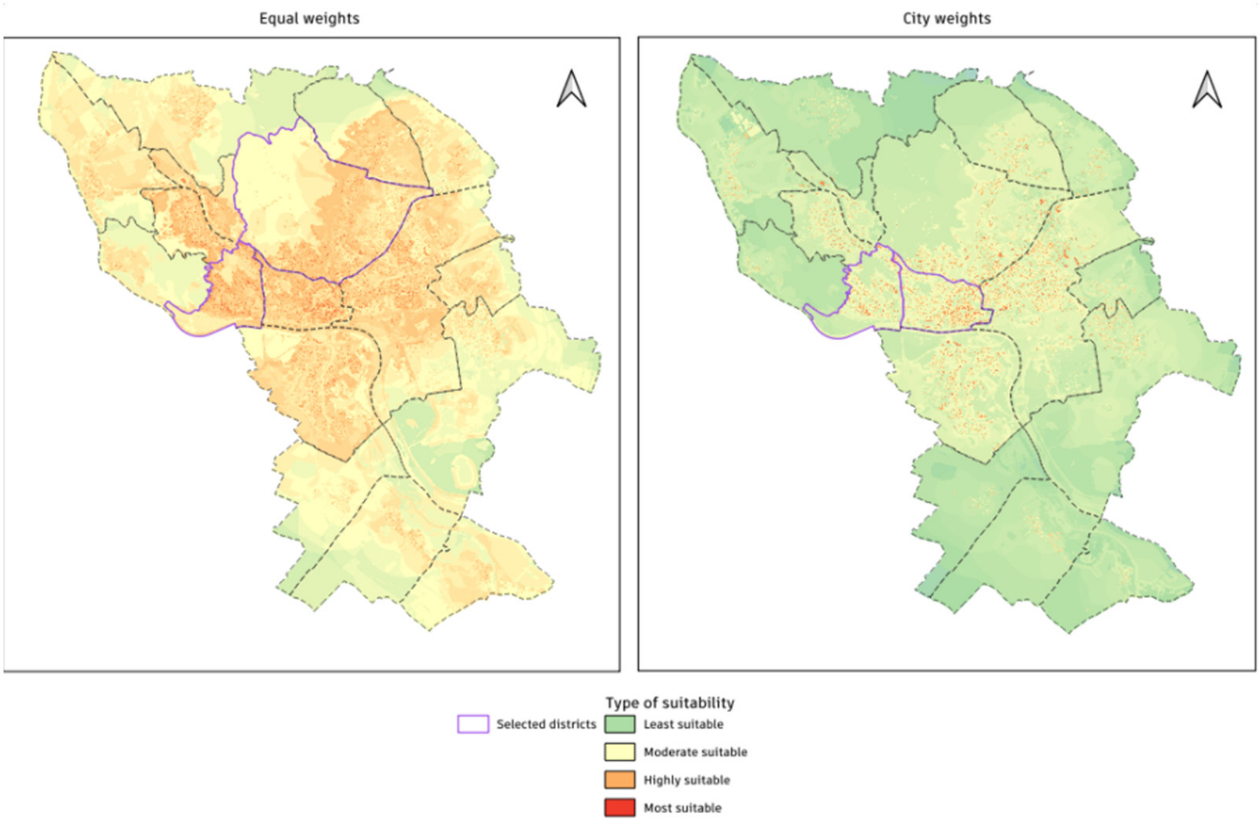


**Figure 5.** Location of the most suitable district for PED implementation. Grey dashed lines represent districts in Bratislava municipality.

As part of the suitability index generation process, the MCDA algorithm also produces the normalized dimensions in raster format, with a spatial resolution of 5 m, matching the same resolution as in the suitability index. These raster layers are stored in the algorithm working repository as functional variables to be represented. These raster files can be of great interest for analyzing and understanding the factor or factors behind the resulting suitability index value. It should be noted that these dimensions are the result of an aggregation process using a weighted mean, so knowing the value of each dimension can be essential when determining the specific weight of each dimension for generating the final suitability index. Some examples of these raster files that represent the dimensions are provided in Figures 6 and 7.

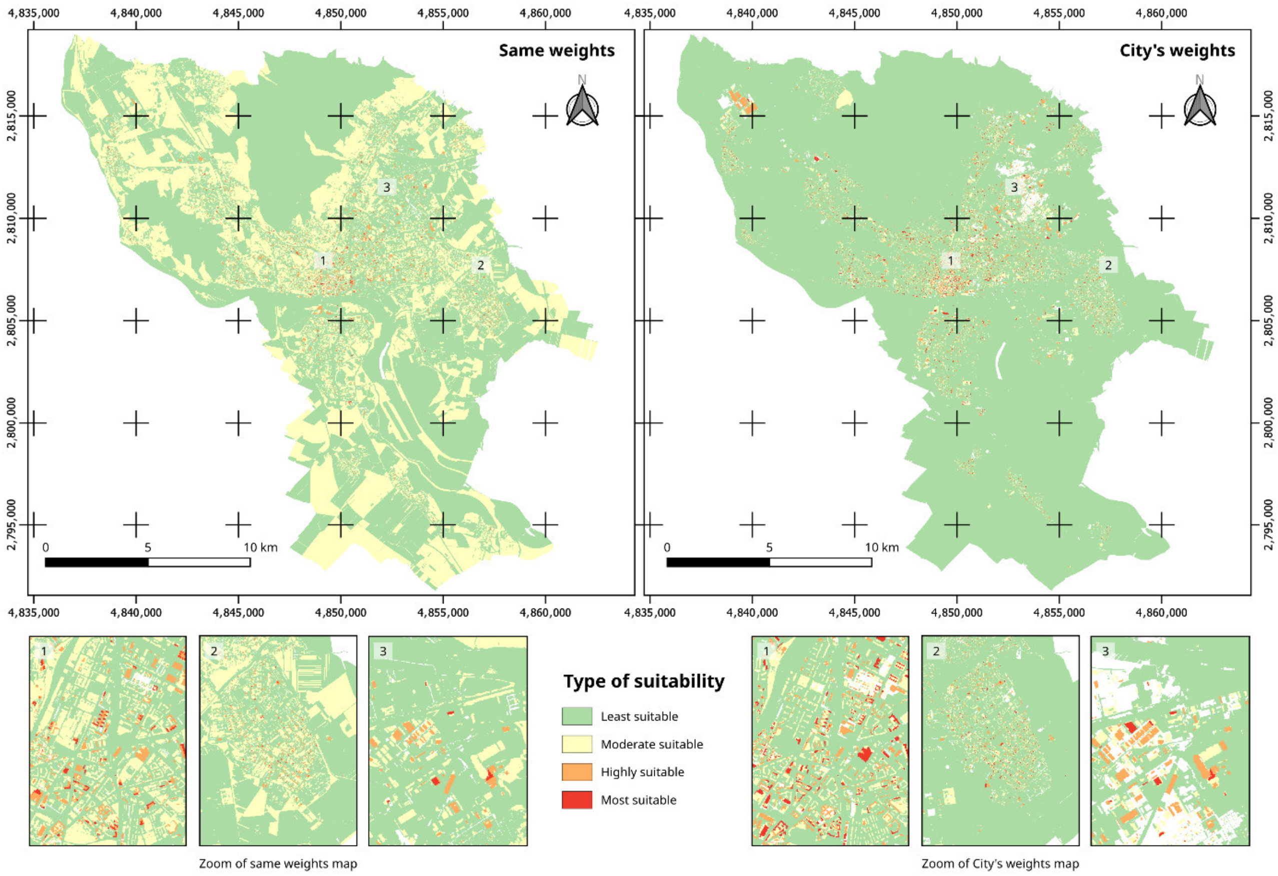


**Figure 6.** Suitability classes for Net zero energy imports dimension: equal and user defined weights. Numbers 1, 2 and 3, represent areas of the municipality with a higher zoom level.

Figure 6 illustrates the suitability classes of the Net zero energy imports dimension under equal and city-specific weighting schemes. The application of city-defined weights results in a more selective spatial classification, with several areas shifting to lower suitability in line with Bratislava's prioritization of energy demand and local renewable energy options. At the same time, areas with favorable demand–supply characteristics maintain higher suitability across both scenarios. Overall, the figure shows how weighting choices shape spatial selectivity while preserving the identification of core high-potential areas for PED development.

Figure 7 compares the suitability classes of the energy flexibility dimension. Under equal weights, suitability is more evenly distributed, with large portions of the city classified as moderately to highly suitable. When city-defined weights are applied, the spatial pattern becomes more selective, with a clearer concentration of highly and most suitable areas and a reduction in suitability in other zones. Overall, the figure illustrates the strong influence of weighting choices on the spatial expression of energy flexibility potential.

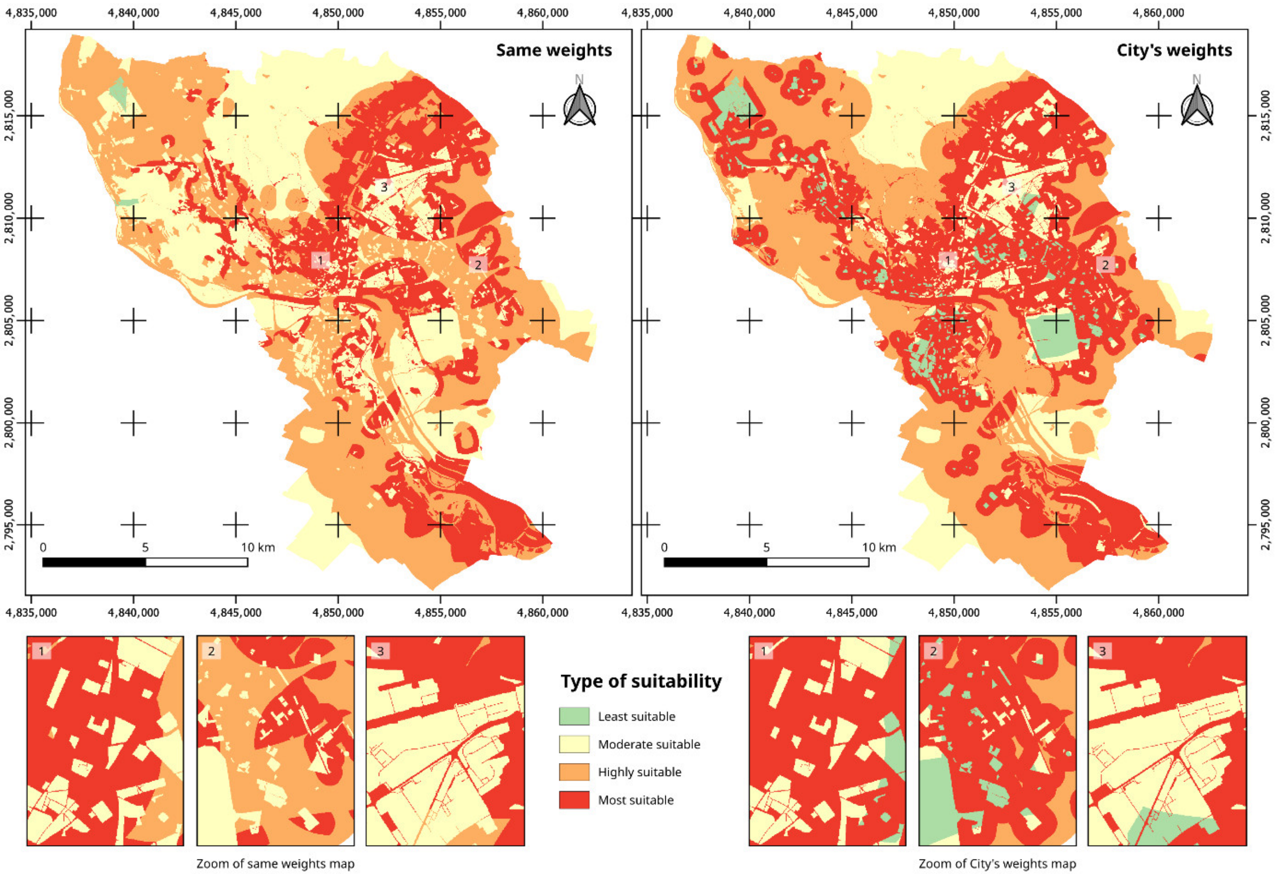


**Figure 7.** Suitability classes for Energy flexibility dimension: equal and user defined weights. Numbers 1, 2 and 3, represent areas of the municipality with a higher zoom level.

## 5. Discussion

The Bratislava case study illustrates how the proposed MCDA framework based on geolocated data can operationalize the concept of Positive Energy Districts by translating high-level PED dimensions into spatially explicit suitability patterns. The comparative analysis between the equal-weights baseline and the city-specific weighting scenario shows that the weighting configuration substantially affects absolute suitability values and the spatial extent of high-scoring areas, but with a moderate effect on the relative ranking of districts. Staré Mesto and Karlova Ves remain consistently among the most suitable districts in both scenarios, while others, such as Podunajské Biskupice, experience notable shifts in ranking when priorities under local knowledge are introduced in the PED assessment. This confirms that the underlying spatial structure of opportunities and constraints is relatively robust, whereas the selection of weights acts as a powerful lever to adjust priorities within that structure [8].

These findings are consistent with the broader PED literature, which emphasizes both the importance and the difficulty of defining operational assessment frameworks around the PED concept. Previous work has stressed that strict annual positive energy balances can be a demanding requirement, especially in dense urban areas with limited local renewable potential, and has recommended broader assessment schemes that combine energy, environmental, economic and social indicators [6,19]. By constructing the five dimensions (efficient buildings, net zero energy imports, energy flexibility, affordability and livability) the proposed MCDA approach aligns with these recommendations and offers a concrete way to integrate multiple performance aspects into a single spatial index. In particular, the inclusion of affordability and livability dimensions responds to calls

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to frame PEDs as socio-technical systems that must address resilience, social equity and quality of life, rather than only optimized energy balances [4,5].

The observed stability of the district ranking across weighting schemes also links to the discussion on PED typologies and context-dependency. Some authors, like refs. [5,10], highlight that PED designs are strongly shaped by local building stocks, infrastructures and institutional conditions, and that not all districts can realistically become fully energy positive. In Bratislava, central districts such as Staré Mesto and Karlova Ves exhibit high suitability in both scenarios, largely due to a combination of dense building stock (and thus high rooftop PV potential) and favorable values in several socio-economic and urban-form indicators. This suggests that the proposed MCDA framework can help to reveal potential PED candidates that align with previous qualitative insights into where PEDs are most likely to emerge [10], while still allowing planners to adjust emphasis through weights.

From a methodological perspective, the results reinforce well-known properties of MCDA supported with GIS data: suitability patterns are highly sensitive to the choice of criteria and weights, and weight definition should be an explicit and participatory process [8,29]. The comparison between the equal-weight scenario and the city-specific scenario shows that stakeholder-defined weights make the suitability landscape more selective, concentrating high scores in fewer districts and downgrading others that do not match Bratislava's priorities (e.g., emphasis on energy demand, available PV rooftop potential and geothermal potential). This behavior is consistent with sensitivity analyses in land suitability studies, where small changes in weights can substantially alter the extent and fragmentation of suitable areas [30]. The explicit combination of map-based visualization with aggregated mean values by district is therefore a strength of the proposed approach, as it supports both spatial interpretation and quantitative comparison, helping to detect cases where small visual differences may hide significant numerical changes, or the opposite situation.

The Bratislava application also extends previous PED-mapping efforts like [16], where they demonstrated the potential of GIS–MCDA for identifying PED boundaries by combining resource availability, infrastructure and socio-economic layers. However, their approach faced limitations related to data availability and harmonization across cities. The present study builds on that work by (i) explicitly structuring the assessment around five PED-related dimensions that can be reused in other cities; (ii) developing the PED identification approach in an open-source Python pipeline based on GeoJSON and standard European datasets (e.g., CORINE Land Cover (CLC) [20], Urban Atlas Land Cover [22], PVGIS [30]); and (iii) emphasizing replicability and transferability from the outset, in line with the gaps identified by [6,7,19]. As a result, this paper obtains a methodology that not only provides city-specific results for Bratislava but can also be integrated into broader replication strategies, to cover the identification of potential PEDs in other cities.

In relation to PED design and planning frameworks, the proposed methodology complements developments such as tools for PED planning [10] or the PED assessment schemes of [6]. While those contributions focus on defining process steps, assessment methodologies and key performance indicators, the present work adds a spatial screening component that can support early-stage decisions on where to concentrate more detailed analyses, simulations or co-design processes. In practical terms, the suitability maps and district-level rankings can be used to narrow down candidate areas for in-depth PED feasibility studies, energy modeling or participatory workshops, thereby helping municipalities with limited analytical capacity to focus their efforts where the combination of technical potential and socio-urban conditions are most promising.

It is necessary to highlight that the inclusion of affordability and social cohesion indicators contributes to operationalizing the socio-technical perspective highlighted in recent PED literature [4,5]. By incorporating variables such as energy expenditure, income, vulnerability and population dynamics, the framework makes possible the prioritization of areas where PED interventions could contribute simultaneously to decarbonization, contributing at the same time to include energy poverty or social vulnerability aspects. This is aligned with the growing recognition that PEDs should also support just and inclusive energy transitions, rather than only delivering aggregate energy or emissions benefits [5].

Despite these strengths, several limitations have been identified. First, the approach relies on the availability and quality of spatial datasets, which may vary substantially between cities. Although the use of open and harmonized European datasets enhances transferability, key variables like detailed building energy demands, local socio-economic statistics or investment plans still require city-specific data collection and modeling efforts. This data dependency is consistent with challenges reported in other GIS-based energy planning studies [9,11–13,16]. This could be an obstacle for the algorithm's application in cities with limited data infrastructure. Second, the current implementation is essentially static: it captures PED suitability under present conditions and does not model temporal dynamics such as demand evolution, climate change impacts, or technology cost trajectories. Extending the framework to incorporate scenario-based temporal analyses or coupling it with dynamic energy system models would provide a more comprehensive basis for long-term PED strategies, as suggested by [6,19].

Third, it is necessary to highlight stakeholder engagement as a tool to create consistent end results. Stakeholder involvement has been included through the definition of city-specific weights, the diversity of stakeholders being key to improving the obtained results. The involvement of technical experts, in addition to citizens, technology providers, and other local actors, could further enrich the weighting process, strengthen the legitimacy of the results, and better reflect the multi-actor governance challenges documented in PED projects [4,10]. Finally, the suitability index is an integrative but simplified representation of complex realities. It does not explicitly account for network constraints, detailed regulatory barriers, or project-level financial feasibility, which will need to be addressed in subsequent PED deployment phases.

Overall, the obtained results confirm that the proposed MCDA framework based on geolocated data responds directly to several gaps identified in the PED literature, such as the need for spatially explicit, replicable methodologies for PED site selection [5,7,16,19], the integration of technical and socio-economic dimensions in PED definition [4,5], and a better understanding of how weighting choices influence spatial prioritization [6,8,31]. By providing both maps and aggregated indicators, and by implementing the full workflow in an open and modular Python pipeline, the methodology offers a practical tool that municipalities can adapt to their own contexts. Future work will focus on expanding the framework for its application to additional cities, testing the effect of different weights in indicators and dimensions, and explore the capacity to integrate dynamic variables in defining potential areas for the implementation of a PED, in addition to moving towards participatory planning processes for PEDs.

## 6. Conclusions

This study has addressed the two research questions posed in the introduction by demonstrating both the capabilities of GIS-based methodologies for PED spatial planning and the conditions that affect their replicability across different urban contexts.

Regarding the GIS-based methodology, the proposed GIS-based MCDA algorithm proves to be an effective and transparent framework for integrating heterogeneous spatial datasets relevant to PED planning. The obtained results highlight that the framework enables a flexible and transparent integration of heterogeneous spatial datasets relevant to PED planning. In addition, they underline the importance of combining spatial visualization with aggregated indicators, such as mean suitability values, to fully understand the implications of weighting choices. By applying and comparing alternative weighting strategies for PED layers and dimensions, the methodology illustrates how suitability maps can be systematically adapted to different planning objectives. Incorporating local knowledge into weighting schemes, it also enhances policy relevance and helps ensure that PED strategies are not only technically sound but also contextually grounded and socially meaningful.

In relation to the second research question, the findings indicate that replicability is primarily driven by the availability and coherence of spatial datasets, the selection of indicators, and weighting schemes reflecting local priorities. Although absolute suitability values vary when city-specific weights are applied, the relative ranking of districts remains largely stable. This robustness reveals a strong spatial coherence in the underlying geolocated, infrastructural, and socio-economic patterns that shape PED potential, regardless of specific weighting assumptions. Such spatial stability increases confidence in the identification of high-priority areas and supports the transfer of the methodology across cities, provided that local data and planning objectives are appropriately incorporated.

Overall, the study demonstrates that alternative weighting strategies can substantially reshape the spatial distribution of PED suitability while preserving consistent relative spatial patterns. The comparison between a neutral, equal-weight configuration and a context-sensitive, city-prioritized scenario illustrates how stakeholder assumptions influence planning outcomes. The equal-weight model offers a balanced and inclusive overview suitable for preliminary screening and stakeholder engagement, whereas the city-specific weighting scheme produces a more selective and strategically focused suitability pattern aligned with real-world decision-making needs.

Finally, the PED modeling framework presented in this study offers a transferable, open-source methodology that other cities can adapt to their own data, priorities and institutional settings to identify their most suitable areas for PED implementation. In this sense, it provides a practical contribution to the emerging toolbox for PED planning, supporting cities that seek to navigate the spatial complexity of PED implementation in line with their long-term climate and urban development objectives.

Future research should further expand the proposed GIS-based MCDA framework by exploring dynamic and multi-temporal datasets to enhance the spatial identification of PED-suitable areas under evolving urban, energy, and climate conditions. In accordance with this, integrating time-dependent variables, for instance, renewable generation profiles, demand evolution, and urban development scenarios, could improve the capacity of GIS-based methodologies to support long-term PED planning and adaptive decision-making. Additionally, the incorporation of participatory approaches and multi-actor weighting mechanisms would allow for a more systematic representation of stakeholder preferences within the spatial analysis.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| GIS | Geographical Information System |
| MCDA | Multi-Criteria Decision Analysis |
| PED | Positive Energy Districts |
| EU | European Union |
| ATELIER | AmsTErdam BiLbao cItizen drivEn smaRt cities Horizon 2020 European project |
| RES | Renewable Energy Sources |
| DHW | Domestic Hot Water |
| EPBD | Energy Performance of Buildings Directive |
| LiDAR | Light Detection and Ranging |
| DTM | Digital Terrain Model |
| DSM | Digital Surface Model |
| LAI | Leaf Area Index |
| OSM | OpenStreetMap |
| PVGIS | Photovoltaic Geographical Information System |
| PV | Photovoltaic |
| CRS | Coordinate Reference System |
| ETRS | European Terrestrial Reference System |
| LAEA | Lambert Azimuthal Equal-Area |
| EPSG | European Petroleum Survey Group |
| CLC | CORINE Land Cover |

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