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ORIGINAL PAPER

Suitability modeling and sensitivity analysis for biomass energy facilities in Turkey

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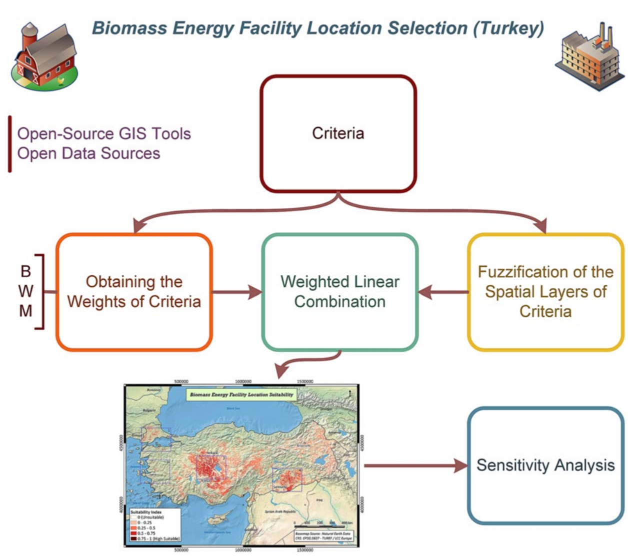
Abstract
Nowadays, problems relating to the inadequacy of energy resources are emerging, due to fast population growth and inevitable urban sprawl. Renewable energy resources are of vital importance in order to overcome these problems that endanger countries in terms of economic, social, and environmental factors. The determination of suitable facility locations is a key matter to solve, in order to effectively exploit biomass energy potential. This paper proposes an approach to biomass facility location that integrates open-source geographic information systems (GIS), fuzzy logic, and a best worst method (BWM) solution, which is a newly developed multi-criteria decision-making (MCDM) method to address optimal facility location. Suitable locations take different criteria into consideration, including potential biomass amount (e.g., agricultural and animal wastes), slope, and distances to roads and water bodies. By utilizing MCDM, the most critical criterion can be determined. Moreover, the paper demonstrates that fuzzy logic allows intermediate values for suitability criteria and is preferable to Boolean logic. The proposed approach is illustrated using all cities of Turkey as an empirical case study. Four specific regions that greatly have highly suitable areas are presented. Sensitivity analysis shows that different agendas such as economic cost and social impact might change the suitability results, specifically in areas of the highly suitable class. These results are most strongly affected by potential biomass amount, population density, and distances to roads and settlements.

Graphic abstract



Keywords Biomass energy · Open-source geographic information systems (GIS) · Best worst method (BWM) · Fuzzy logic · Suitability modeling · Turkey

Extended author information available on the last page of the article

Introduction

Energy is indispensable for the development and welfare of countries. Fossil fuel energy production persists even though its consumption damages the environment and contributes to global warming especially in areas of population growth and an increase in industrialization (IEA (International Energy Agency) 2018; EIA (U.S. Energy Information Administration) 2019). In 2018, while fossil fuel consumption globally ranked highest (79.9%) among energy sources, energy consumption from modern renewable energy sources (defined as wind, solar, geothermal, ocean power, hydropower, and biomass) was only 17.9% collectively (REN21 2020). Replacement of fossil fuel with renewable energy sources is argued to reduce harmful gas emissions and satisfy growing demand (Abdul Malek et al. 2020). Increased use of renewable energy sources can also reduce foreign dependencies in several countries, for example, Brazil (Guerini Filho et al. 2019), Bangladesh (Masud et al. 2019), and Poland (Igliński et al. 2015). It is expected that renewable energy sources will play an important role in coming decades (BP 2020).

Biomass is of vital importance to sustainable energy production because (in contrast to solar and wind sources) it is a steadily reliable source that can provide a base-load energy supply. Any renewable or organic by-products from crops/plants and animals can be defined as biomass, including residues of husbandry, agriculture, and forestry (DoE (U.S. Department of Energy) 2020). In other words, biomass can be described as a naturally occurring material that is directly used as a fuel or easily converted to biofuel. Biomass can be used to generate electricity and heat by applying different conversion techniques such as gasification and anaerobic digestion (WEC 2016).

This paper examines the adoption of biomass renewable fuel sources using Turkey as a case study. This country provides an example of the complexities of situating biomass production and transitioning from fossil fuel as a primary energy source. Turkey is located between southeastern Europe and western Asia. Its geographical location provides an energy bridge of fossil fuel between Middle East countries and Europe (Melikoglu 2017). Turkey provides a large study area (783,562 km^2). Fossil fuels (principally coal and natural gas) account for a large portion of the energy consumption of Turkey. The net electricity consumption in Turkey is gradually increasing due to exponential population growth, urbanization, and economic development (TurkStat 2020). Concurrently, greenhouse gas (GHG) emissions are also growing considerably.

Another factor justifying the Turkey case study is the recent adoption of policies favoring regulated transition toward renewable energy. Energy security becomes a significant issue for Turkish policies aiming to reduce foreign dependence on fossil fuels. The government recently announced goals to diversify energy (IOPRT 2021). These goals will increase the percentage of renewable sources in the energy sector, decrease harmful gas emissions, and reduce dependence on fossil fuel imported from other countries. The 11th Development Plan (PRT 2019) intends to increase renewable energy shares in electricity production to 38.8% by 2023.

A third factor is that Turkey has a notable production potential for biomass energy (Toklu 2017). The total biomass energy potential of the country was predicted on average at 17.0 Mtoe (million tons of oil equivalent) per annum. The energy potential from animal waste and agricultural residues was recently calculated as 23,760 terajoule (TJ) (Melikoglu and Menekse 2020) and 998,473 TJ, respectively (Avcıoğlu et al. 2019). For all of the reasons described above, determination of suitable locations for biomass energy facilities becomes crucial to exploit the renewable energy potential of Turkey. The objective of this paper is to obtain a suitability index for locating potential biomass energy facilities in Turkey for future adoption as one source of renewable energy.

The locations of biomass energy facilities should take into account economic and environment parameters. For example, biomass facilities should be located at specific distances from road networks to optimize transportation efficiency (Zheng and Qiu 2020). Also, the suitable locations must follow constraints that are indicated in regulations to protect the environment (Bojesen et al. 2015).

Geographic information systems (GIS) technology provides a powerful tool to assess suitability for biomass energy facilities, since it offers a number of strategies to manipulate both spatial and semantic data (Díaz-Cuevas et al. 2018) in order to meet multiple constraints. For example, Sahoo et al. (2018) assessed the location suitability for bioenergy facilities using GIS-based location–allocation analysis in Ohio, USA. Zareei (2018) found suitable sites for a biogas plant in Iran using GIS-based overlay analysis. Van Holsbeeck and Srivastava (2020) proposed possible locations for bioenergy conversion facilities in Queensland, Australia, by means of GIS-based local index of spatial autocorrelation (LISA) analysis. Latterini et al. (2020) found suitable locations for small-size biomass plants in Lazio, Italy, using a GIS-based approach. Díaz-Vázquez et al. (2020) selected suitable locations for anaerobic digesters in Mexico using GIS overlay analysis after evaluating the biogas potential from livestock manure.

Multi-criteria decision-making (MCDM) methods applied in a GIS environment can quantify the relative importance of various environmental and social criteria (Uyan 2017; Li 2018; Aydin and Sarptas 2020; Settou et al. 2020; Barzehkar et al. 2020). GIS-based MCDM and variants have been relied upon to rank optimal locations for bioenergy plants in

Colombia (Rodríguez et al. 2017), Japan (Babalola 2018), Spain (Jeong et al. 2017; Díaz-Cuevas et al. 2019), Brazil (Costa et al. 2020), Australia (Jayarathna et al. 2020), Iran (Davtalab and Alesheikh 2018), Italy (Famoso et al. 2020), Tasmania (Woo et al. 2018), and Nigeria (Chukwuma et al. 2021). In Turkey, GIS and MCDM methods have been demonstrated for several local studies in the Aegean region (Cebi et al. 2016), in several cities (Yuruk and Erdogmus 2018; Yücenur et al. 2020; Yalcinkaya 2020; Gital Durmaz and Bilgen 2020). One contribution of this paper differs from previous studies in using GIS and MCDM to examine the entire nation of Turkey, rather than creating suitability models for localized study areas.

The work reported here also incorporates three methodologies that have not been incorporated in previous suitability assessments. First is the use of fuzzy logic, which can represent the complex spatial characteristics of decisive criteria more realistically than deterministic functions. Second is the use of open-source GIS software to make modeling parameters and workflows transparent, ensuring reproducibility and replicability (Kedron et al. 2020). A third methodology is the best worst method (BWM), a type of MCDM that operates on relative ranking to generate weights. BWM has been used in some recent suitability studies (Kheybari et al. 2019; Wu et al. 2019) albeit without integration with GIS or fuzzy logic.

The results shown here report a first study on biomass energy facility location selection using a holistic approach that integrates open-source GIS, BWM, and fuzzy logic and applies that approach to an entire nation. The approach can be replicated easily in other locations and can accommodate varying administrative policies as well as alternate sets of criteria. Additionally, the utility of fuzzy logic permits expansion of candidate sites in the event that no single location meets all criteria fully. A sensitivity analysis is presented to demonstrate how the work can also benefit the planning process in validating where modeling outcomes are stable under differing agendas and priorities.

Research methodology

This study finds suitable locations for biomass energy facilities by integrating GIS, BWM, and fuzzy logic techniques. GIS is used to conduct enhanced spatial analyses and spatial data manipulation, while MCDM methods enrich the trustworthiness of the analysis. Fuzzy logic (rather than Boolean logic) is used to quantify uncertainty and establish the relative importance of each criterion. The implemented workflow is shown in Fig. 1.

The analysis is divided into three parts. In the first part, a BWM analysis allows the decision-makers to create comparison matrices by ranking the relative effectiveness of each criterion. The criteria can have values in different units such as meter, kilometer, and percentages. The criteria are ranked by assigning weights according to specific agendas (e.g., pro-development, pro-environment, etc., as described below). Weights are normalized into a 0–1 range, relative to the most important (best) and least important (worst) weights. Once normalized, weights are averaged for each criterion. The BWM will be demonstrated in the analysis to show how weights are selected, normalized, and averaged.

In the second part of the methodology, threshold values related to each criterion are determined in relation to their suitability to biomass facility location, taking literature and regulations into account. Fuzzy logic (Zadeh 1965, 1997) is utilized to assign a numeric probability for threshold values and to permit some flexibility in identifying spatial extents for each criterion. For example, facility locations should be situated neither too far nor too close to water bodies. Although it is not a familiar phrase in popular language, "fuzzification" and "defuzzification" have appeared in recent literature on remote sensing applications (Hofmann 2016). Several membership functions can be selected depending on the characteristics of the studied case. In this study, S-shaped and linear functions are used to conduct fuzzification of spatial layers from determined threshold ranges (Guler and Yomralioglu 2021), creating raster layers for each criterion by reclassifying pixels with probabilities assigned from the fuzzified membership functions.

The third part of the analysis involves weighted linear combination (WLC) and GIS overlay of probability layers to obtain the location suitability index. WLC multiplies pixel values of each criterion layer by its fuzzy probability, summing values to derive a suitability index. Suitability indices may be classed. The final result is obtained by extracting constrained areas from the study area that fall within the most suitable class ranges.

In this study, all spatial analyses are executed by using open-source GIS tools, namely QGIS (QGIS Development Team 2021), SAGA (SAGA Development Team 2021), GRASS GIS (GRASS Development Team 2021), and GDAL (GDAL/OGR Contributors 2021). Tools for this study that are created in the QGIS environment are publicly available for the interested readers (Guler et al. 2021).

Criteria and data sources

For this study, all criteria and thresholds are drawn from the published literature (Table 1). For localized case studies, scholars investigated the renewable energy-related legislation in specific jurisdictions to determine suitable locations for biomass facilities. The research reported here was limited to choosing from existing criteria in past studies because, to the best of the authors' knowledge, there is no uniform

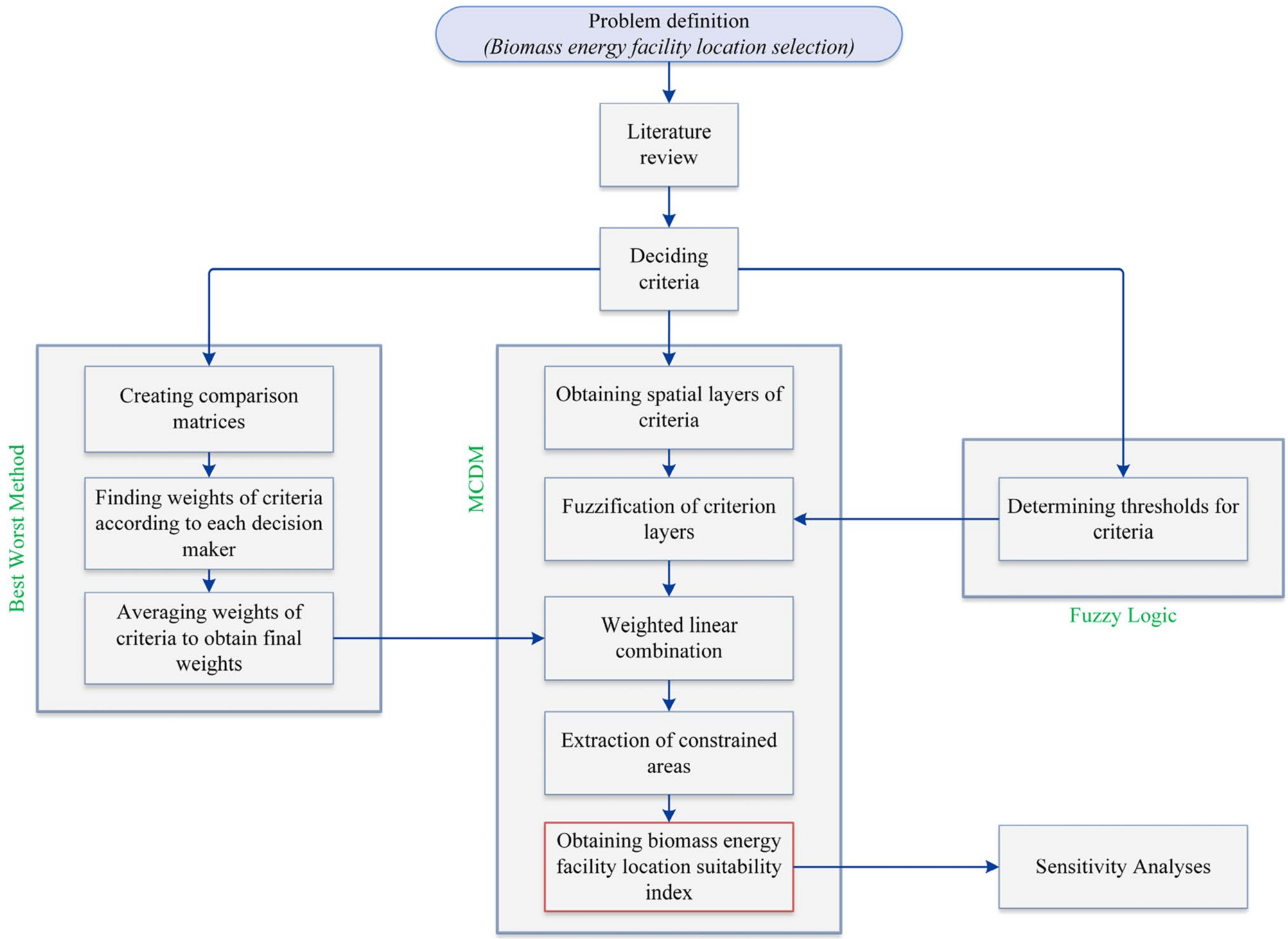


Fig. 1 The methodology implemented in this study

Table 1 The criteria used in this study and their acronyms. Estimated biomass energy based on agricultural and animal wastes is measured in petajoules (PJ), and proximity values are measured in meters (m)

Acronym	Criterion	References
C1	Population density (people per km^2)	Jayarathna et al. (2020), Silva et al. (2017), Franco et al. (2015)
C2	Estimated biomass energy (PJ)	Costa et al. (2020), Jayarathna et al. (2020), Wu et al. (2019)
C3	Slope (%)	Costa et al. (2020), Jayarathna et al. (2020), Famoso et al. (2020)
C4	Proximity to a water body (m)	Costa et al. (2020), Famoso et al. (2020), Gital Durmaz and Bilgen (2020)
C5	Proximity to road network (m)	Costa et al. (2020), Jayarathna et al. (2020), Gital Durmaz and Bilgen (2020)
C6	Proximity to railway network (m)	Zareei (2018), Sahoo et al. (2018), Costa et al. (2020)
C7	Proximity to settlement area (m)	Costa et al. (2020), Famoso et al. (2020), Gital Durmaz and Bilgen (2020)

legislation in Turkey to follow in choosing optimal locations of biomass facilities.

The seven criteria in Table 1 are used in BWM calculations. In this step, spatial data that represent the criteria and constraints are created, using open-source information. Spatial data are available across a range of resolutions (10–100 m). Data layers are resampled to 100 m resolution to harmonize the resolutions of multiple data sources to a common level.

The *population density* (C1) computed as people per square kilometer evaluates the demand for biomass facilities. Areas with high population density are more suitable for biomass facilities because the energy can be transported to these areas easily. Also, these areas likely need more energy, due to higher demand. The 2018 population data were obtained from the Turkish Statistical Institute in tabular form (TurkStat 2019). Spline interpolation creates a final interpolated surface at 100 m resolution for the whole country.

The *estimated biomass energy* (C2) values determine potential biomass energy yield from animals and crops/plants. Areas with high biomass production can provide a higher concentration of waste to a biomass facility. Information for 2014 is provided through the General Directorate of Energy Affairs of Turkey (MENRRT 2014). The data source contains potential bioenergy values that can be obtained from different kinds of animal and agricultural residues. Spline interpolation is used again to create a national potential yield surface of biomass energy.

The *terrain slope* (C3) can affect biomass facility construction costs and the difficulty of site preparation. Turkey has several regions with steep slopes, and the areas with lower slope are evaluated as more suitable. Slope data are derived at 100 m from the 25 m European Union Digital Elevation Model (EU-DEM) (EUC 2016). The *proximity to a water body* (C4) is an important factor for location selection due to environmental impact and facility management. In this study, the criterion includes surface water but not groundwater proximity. Water quality can be impacted by biomass facilities, and hence, the facilities should not be immediately adjacent. On the other hand, biomass facilities benefit from water availability for processing, and therefore, facilities should not be built too far away from water sources. CORINE (EUC 2019a) land cover data at 100 m are used for this layer.

The *proximity to road network* (C5) plays an important role in transporting waste to a biomass facility. The Global Roads Open Access Data Set (gROADS) (Center for International Earth Science Information Network—CIESIN and Information Technology Outreach Services—ITOS 2013) provides the source create the network of major roads in Turkey. A similar consideration should be made for *proximity to railway network* (C6), since sites that are close to a railway network can offer advantages in terms of transportation. Railway data were drawn from OpenStreetMap (OSM Contributors 2021).

The *proximity to settlement area* (C7) criterion can be used to estimate proximity to population (demand) as well as assessing impacts of a biomass energy facility on residential living environments and service areas. High-resolution (10 m) settlement areas are obtained from the European Settlement Map (EUC 2019b) which is a public data domain from the EU.

Five additional data layers refine the selection of suitable areas. None of these are utilized for criteria weighting. Instead, they are applied in binary form, meaning a discrete threshold is applied. Areas not meeting the criteria are immediately determined to be unsuitable and eliminated from consideration. All four binary criteria carry important environmental protections. The wetland layer and the mining area layer are drawn from CORINE. A layer representing green and protected area layers incorporates data from the Tree Cover Density (TCD) (EUC 2018) dataset from EU and from the General Directorate of Nature Conservation and National Parks of Turkey (MAFRT 2021). Lastly, the airport layer is drawn from the General Directorate of State Airports Authority of Turkey (MTIRT 2021). Figure 2 illustrates the geography of all spatial data layers prepared for this study.

Best worst method (BWM)

BWM is a newly developed and widely accepted MCDM method (Rezaei 2016; Mi et al. 2019). It is based on pairwise comparisons that is a commonly used method in biomass facility site selection studies. BWM carries several advantages over other MCDM methods (Rezaei 2015):

- BWM is a vector-based method that requires a minimal number $(2n-3)$ of pairwise comparisons. In contrast, another MCDM method is AHP that requires $n(n-1)/2$ pairwise comparisons. Fewer comparisons facilitate decision making.
- BWM generates more consistent results in determining criteria weights, since the best and worst criteria are decided at the beginning of the decision process. BWM calculates a consistency ratio in order to check the reliability of decisions. The closer that the consistency ratio is to zero, the more reliable are the decisions.
- BWM uses integer ranks instead of floating-point numbers. This speeds computations and simplifies interpretations.
- BWM allows integration of other MCDM methods to obtain criteria weights, although that integration is not utilized in this paper.

Fuzzification of the spatial layers

Fuzzification in the GIS environment is executed by means of raster-based calculations, controlled by one or multiple threshold values. A number of equations can be used to guide fuzzification, depending on the study area and on the particular criteria. Threshold values used here are determined based upon previously published studies. Four functions will be applied and are shown in the following. In all equations, fuzzified pixel values are represented as $\mu_M(x)$, where x expresses the specific pixel value. Equation (1) shows the linear function with four threshold parameters (a, b, c, d) to stratify pixel membership into suitability levels. The linear equation will be applied to all four proximity-based criteria. Equations (2) and (3) show increasing and

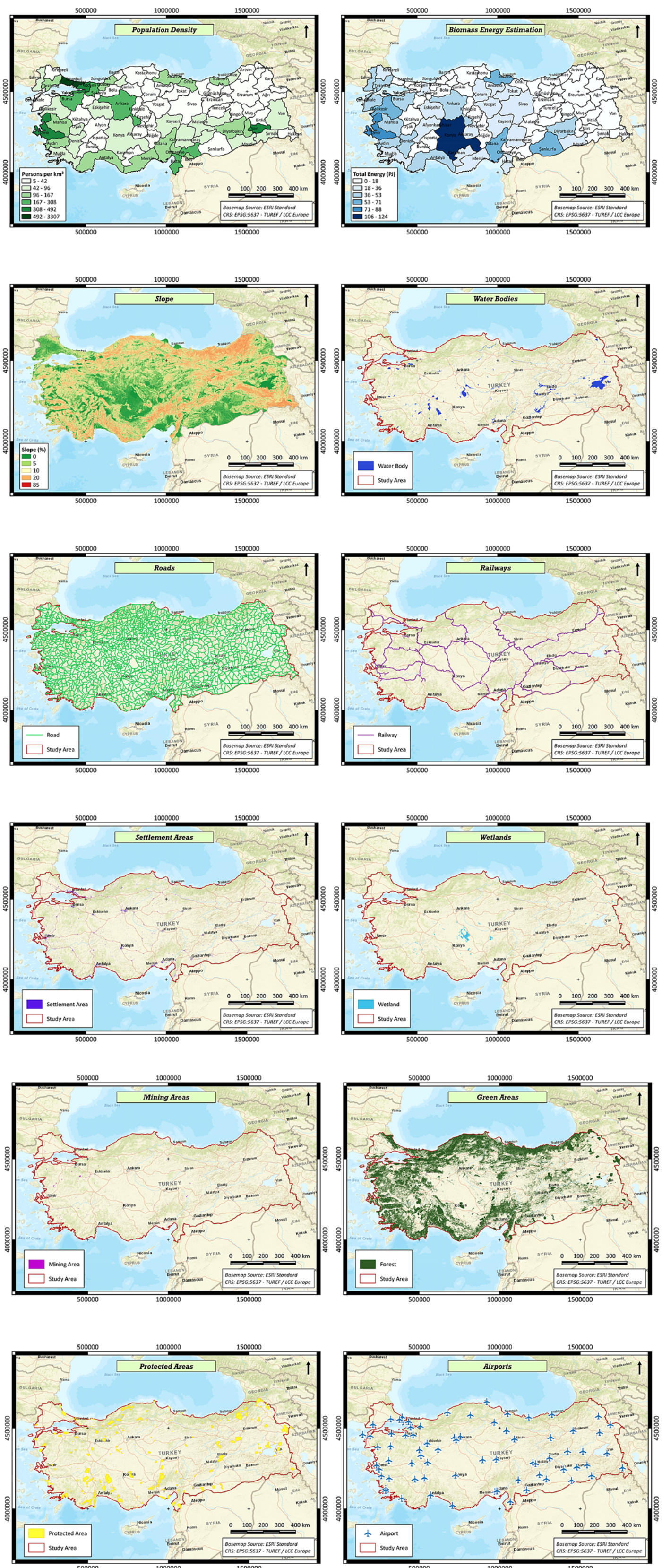


Fig. 2 The spatial data layers that are used in this research. These maps show spatial layers of the seven weighted criteria used in the BWM, and the five binary layers that are used to create a constraint layer. All layers are resampled to 100 m spatial resolution

Table 2 The threshold values of criteria that are used for the fuzzification process

Criterion		Fuzzy threshold values			Function type
		0	0–1	1	
C1	Population density (people per km^2)	<30	30–200	>200	S(i)
C2	Estimated biomass energy (PJ)	<10	10–70	>70	S(i)
C3	Slope (%)	>15	2–15	<2	S(d)
C4	Proximity to a water body (m)	<200, >2000	200–500, 1000–2000	500–1000	Linear
C5	Proximity to road network (m)	<100, >3000	100–500, 1000–3000	500–1000	Linear
C6	Proximity to railway network (m)	<100, >3000	100–500, 1000–3000	500–1000	Linear
C7	Proximity to settlement area (m)	<1000, >5000	1000–1500, 3500–5000	1500–3500	Linear

i increasing, *d* decreasing

decreasing S-functions, respectively. These functions rely on two parameters (a, b), to compose membership. The increasing S-function will be applied to population density and estimated biomass energy, and the decreasing function will be applied to slope.

$$\mu_M(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \le x \le b \\ 1 & b < x < c \\ \frac{d-x}{d-c} & c \le x \le d \\ 0 & x > d \end{cases} \tag{1}$$

$$\mu_M(x) = \begin{cases} 0 & x < a \\ \sin\left(\frac{x-a}{b-a} \times \frac{\pi}{2}\right) & a \le x < b \\ 1 & x \ge b \end{cases} \tag{2}$$

$$\mu_M(x) = \begin{cases} 1 & x < a \\ \sin\left(\frac{b-x}{b-a} \times \frac{\pi}{2}\right) & a \le x < b \\ 0 & x \ge b \end{cases}. \tag{3}$$

Table 2 shows the fuzzy threshold values for each criterion that is used in this study, drawing upon relevant literature as shown in Table 1 and taking features of the study area into consideration.

Weighted linear combination

After deciding the criteria and their threshold values for the fuzzification process, the next step of the spatial analysis is to calculate a biomass facility location suitability index for each pixel in the study area. Weighted linear combination is widely applied in GIS-based suitability modeling studies. Equation (4) shows a formula for linear combination:

$$V(A_i) = \sum_{k=1}^{n} w_k v(a_{ik}) \tag{4}$$

where w_k represents the weight of each relevant criterion and $v(a_{ik})$ expresses the pixel values of the spatial layer of that criterion. In this research, the final suitability index of each pixel in the study area is computed as the multiplied product of fuzzified pixel values and weight of relative criteria, summed across all criteria.

Analysis and results

Comparing among three best–worst criteria weighting methods

For a comparative view of how BWM can operate, the weights of criteria were first determined by three different decision-makers separately and then the average of these three weights was calculated to find a final weight for each criterion. All three decision-makers are GIS researchers with scholarly interest in suitability modeling and sustainable energy. The reader should keep in mind that the purpose of the case study presented here is to demonstrate the BWM method, rather than to achieve a definitive solution to the Turkish facility location. Thus, the three sets of weights are intended to generate a variety of responses rather than to prioritize a single agenda (e.g., pro-development, pro-environment, cost-minimizing, etc.).

It is realistic to assume that decision-makers would approach the topics from a different point of view, which represent differing agendas. For example, while DM1 and DM2 selected C2 (estimated biomass energy) as the best criterion, DM3 chose C5 (proximity to the road network) as the best criterion. All three decision-makers differentially selected the worst criterion, C6 (proximity to the railway

Table 3 The pairwise comparisons composed by DM1, DM2, and DM3

DM1	BO	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Worst criterion: C_6
	Best criterion: C_2	3	1	6	5	4	9	3	
	OW	6	9	2	3	4	1	6	
DM2	BO	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Worst criterion: C_1
	Best criterion: C_2	9	1	2	2	3	5	5	
	OW	1	9	7	6	2	3	2	
DM3	BO	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Worst criterion: C_7
	Best criterion: C_5	2	2	4	5	1	6	9	
	OW	2	6	4	3	9	3	1	

BO Best to others, *OW* others to the worst, *DM* decision-maker

network), C1 (population density), and C7 (proximity to settlement area), respectively. All pairwise comparisons created by decision-makers are shown in Table 3.

Table 4 shows the normalized weights of criteria that are calculated from those pairwise comparisons. The normalized weights sum to 1 for each decision-maker. As mentioned before, BWM enables the calculation of a consistency ratio (CR) for checking the stability of decisions. The consistency ratio determines whether the obtained weights are consistent relative to the best and worst as chosen by a decision-maker. Table 4 indicates that all consistency ratios are less than 0.25, meaning that they are consistent according to the literature (Gómez-Limón et al. 2020).

To find a common ground for different decision-makers, the weights are averaged in MCDM studies. From the column of average weights, one can note that all criteria have different weights. C2 has the highest weight and C6 has the lowest weight. Among the group of decision-makers then, the value of estimated biomass energy (C2) is evaluated as the most important factor that affects the biomass facility location selection, and proximity to railways (C6) is selected as the least important factor.

Obtaining the location suitability index

The next step is the fuzzification of criteria layers using fuzzified threshold values of criteria. The choice of the s-curve or linear model is selected depending on the criterion. Figure 3 illustrates the fuzzified spatial data layers of criteria. As can be seen from the figure, the pixels of all layers have values normalized between zero and one. Pixels with values closer to one have the highest suitability for biomass facility.

Candidate pixels for location selection of biomass facility are determined by summing the product of averaged weights and fuzzified values for all seven criteria, for each pixel. Candidate suitable areas are refined in two steps. A first step considers four binary constraints, including proximity to wetlands, to mining areas and to airports, and proximity to green space and protected areas. Proximity thresholds for the first three are set at 1,000 m, and for the fourth, a threshold of 500 m was defined, again following the published literature. Any pixel not meeting one of the binary criteria is removed from the candidate set. A second step filters the remaining candidates to exclude areas of contiguous pixels that are smaller than 4 ha, reasoning that a suitable site must exceed this size to accommodate processing and infrastructure.

Figure 4 illustrates the final suitability map for biomass energy facility location. The suitability index ranging between zero and one is divided into five classes. Figure 5 shows relative coverage of suitability classes. As is often the case, the regions of highest suitability are much less frequent than regions that are less suitable. This finding demonstrates a real advantage of integrating MCDM and fuzzification, namely that the method can identify location sites that meet all criteria, as well as sites that are nearly optimal and meet some but not all criteria thresholds. Four specific areas are picked to show the suitability locally (Fig. 6).

Area 1 is located in the northwest of Turkey and includes cities such as Edirne, Tekirdag, Balikesir, Bursa, and Istanbul of the Marmara region. This area abounds in biomass energy potential and also has a high population density. The selected area has numerous pixels that have suitable

Table 4 Normalized ranking and averaged criteria weights. The weights always sum to 1 and the consistency ratio (CR) should remain as low as possible, ideally under 0.25 (Gómez-Limón et al. 2020)

Criterion	DM1	DM2	DM3	Average	Rank
C1	0.1502	0.0327	0.1448	0.1092	5
C2	0.3861	0.3350	0.2069	0.3093	1
C3	0.0751	0.1879	0.1034	0.1221	3
C4	0.0901	0.1879	0.0828	0.1203	4
C5	0.1126	0.1062	0.3517	0.1902	2
C6	0.0358	0.0752	0.0690	0.0600	7
C7	0.1502	0.0752	0.0414	0.0889	6
Sum	1	1	1	1	
CR	0.06	0.04	0.06		

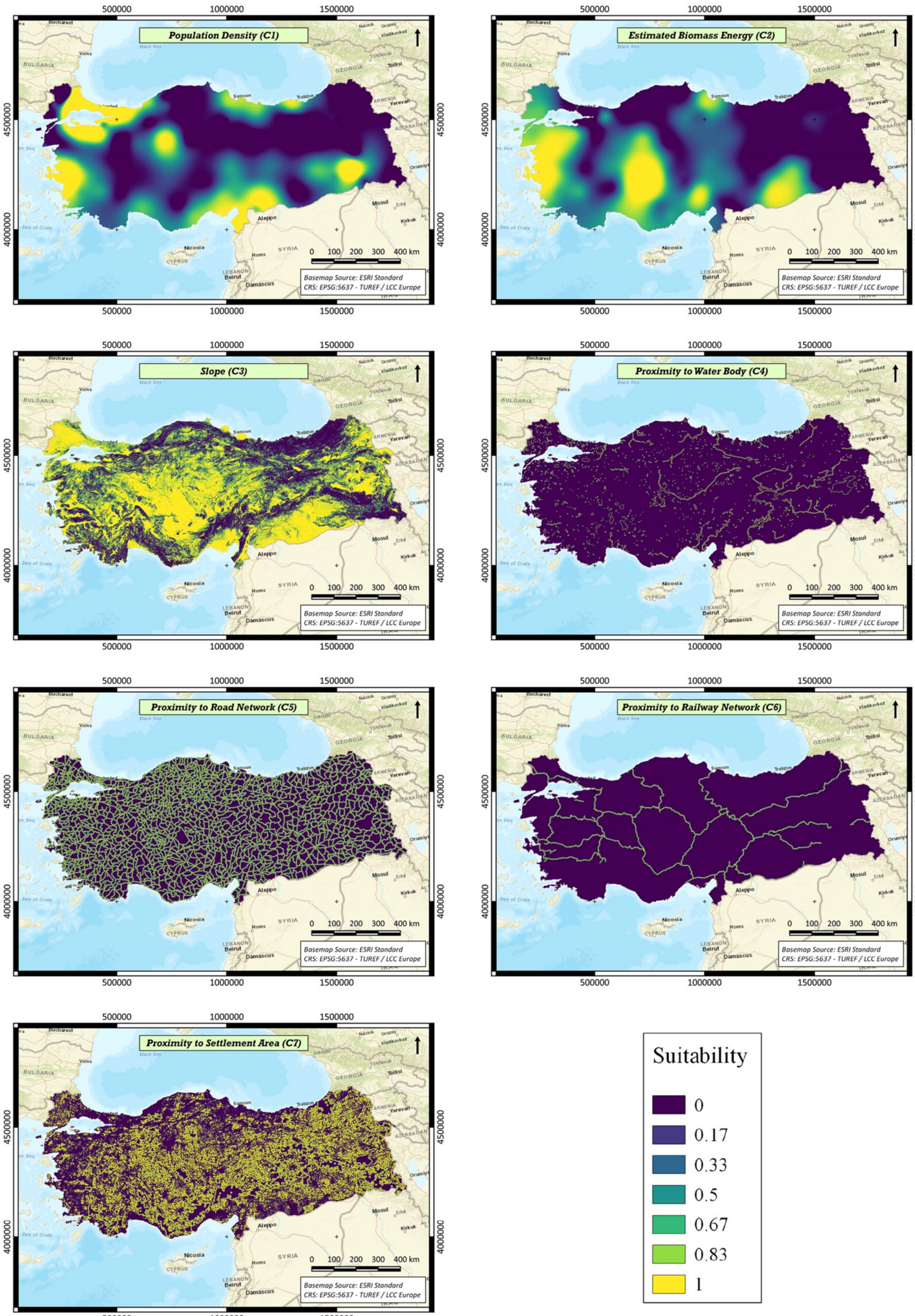


Fig. 3 The fuzzified spatial data layers of criteria that are used in this research

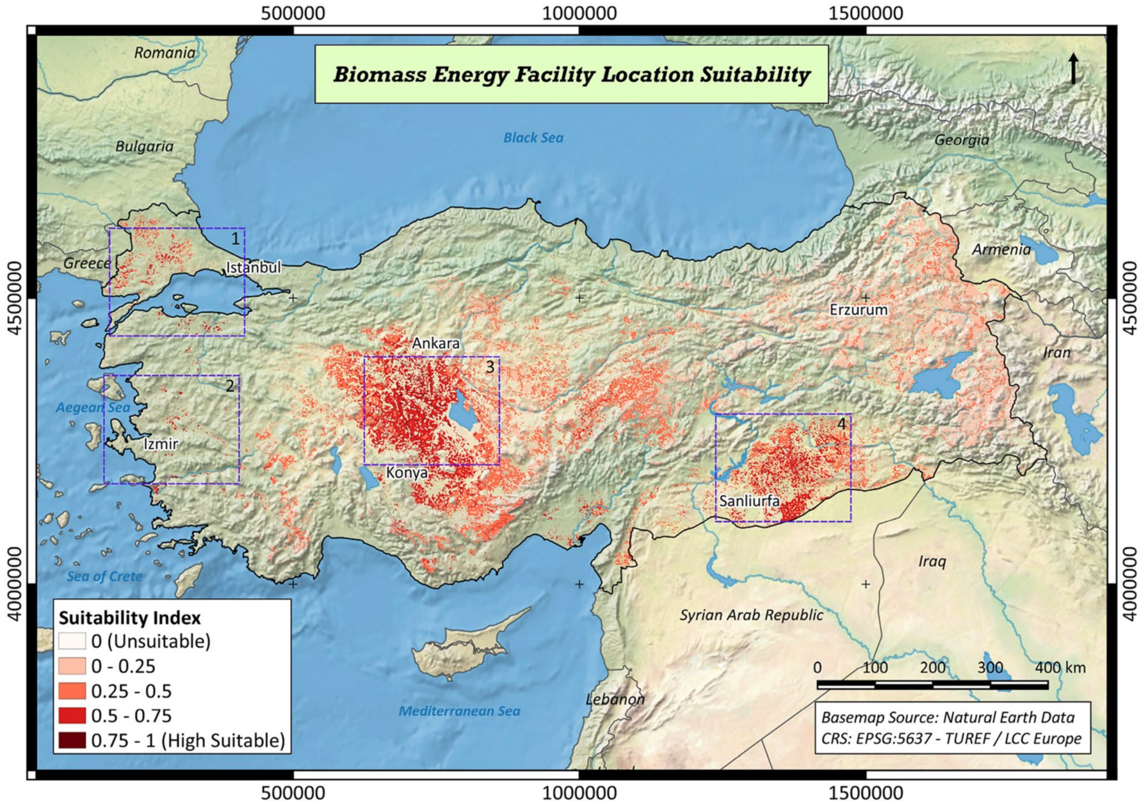


Fig. 4 The final map of biomass energy facility location suitability, accounting for binary constraints and filtering sites with an area greater than 4 ha. Inset boxes refer to the local suitability discussion that follows

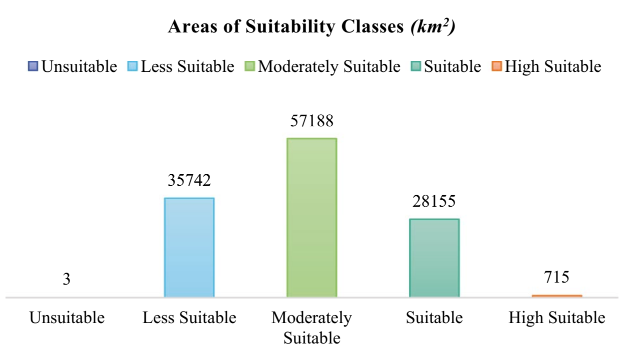


Fig. 5 The areas of suitability classes. These suitability classes correspond to the numeric class ranges in the maps

and highly suitable classes because it does not contain constraints such as forested, green, or protected areas. In addition, it is characterized by lower slope gradients. This area is also close to Istanbul, which carries a high demand for energy. Hence, *Area 1* can be considered a suitable candidate for the allocation of facilities.

Area 2 lies in the west along the Aegean Sea and contains the cities of Izmir, Aydin, and Manisa. The suitability of pixels is due to high potential biomass energy from plant and animal waste. High demand for energy would come from Izmir, the third most populated city in Turkey.

Area 3 lies in the central Anatolia region of Turkey and is mainly composed of the Ankara and Konya cities. This region has large areas of suitable and highly suitable pixels, with lower gradients of slope and with few (binary) spatial constraints. In addition, Konya has the significant advantage of being the first ranked city in Turkey in terms of biomass energy yields. Moreover, the proximity to settlement areas and roads plays a significant role in establishing the large number of suitable pixels.

Area 4 in the southern Anatolia region is composed of the cities Sanliurfa, Diyarbakir, and Mardin. The cities are good candidates transforming waste resources into usable energy. Similar to other selected areas, the slope is relatively flat. It is clear that in all four local areas, the most suitable locations are directly affected by high estimated biomass energy yield values and flatter slopes.

The results of these localized studies concur with Morato et al. (2019) in terms of criteria weights, because biomass energy potential and proximity to road networks, respectively, come first and second in the ranking of criteria. In addition, the obtained results in this research share similarity with another study (Yücenur et al. 2020), since two

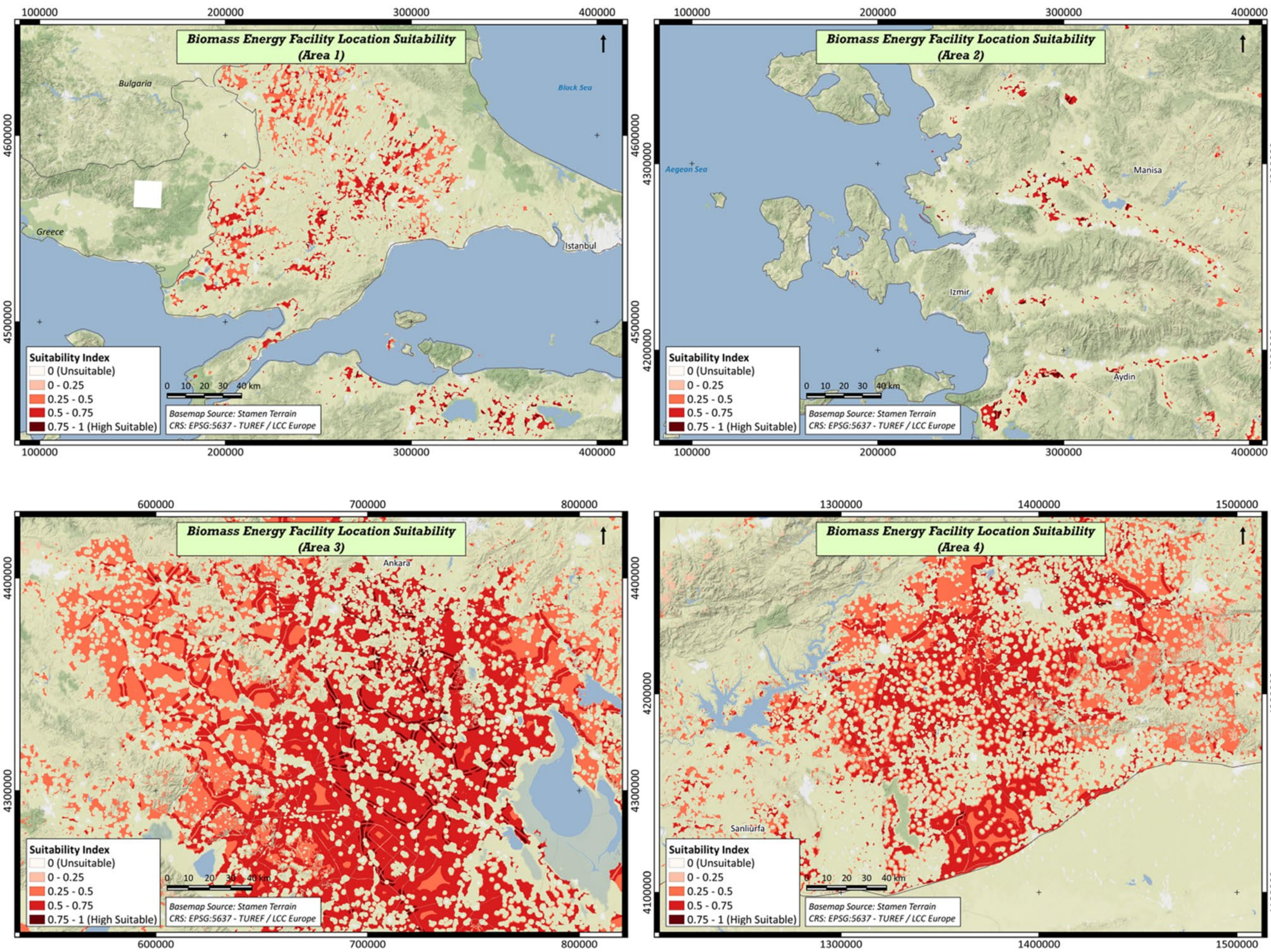


Fig. 6 The inset maps of the areas that are determined for closer examination of suitability

cities, Aydin and Konya, are commonly identified as suitable locations for biomass facility. Other locations in different cities show greater dissimilarities, perhaps because of the utilization of estimated biomass yield that is obtained from the theoretical use of both plant and animal waste. Moreover, the results related to *Area 2* support previous findings (Cebi et al. 2016) identifying the city of Aydin as a suitable location.

Sensitivity analysis

A sensitivity analysis is carried out to reveal possible uncertainties introduced in the study. The sensitivity analysis can identify how responsive is the suitability index to specific agendas or priorities of decision-makers. The sensitivity analysis can present different points of view to policymakers and planners with respect to suitable locations of the biomass energy facilities. The suitability location of renewable energy facilities is usually evaluated in terms of economic, environmental, and social impacts (Barzehkar et al. 2020) because these aspects affect their efficiency. In the analysis, multiple suitability indexes are created by considering different scenarios and form a comparative basis on which to make informed decisions.

Four different scenarios are identified in the present study, each with a different stakeholder agenda. The environmentalist scenario advocates for minimizing impacts on the environment. The social impact scenario promotes social benefit, giving priority to communal benefits such as job opportunities. The economic cost scenario promotes a facility location that balances investment and operational costs. Finally, the developer profits scenario pays attention to obtaining the highest production rate and most efficient transfer of waste.

Criteria ranks for each scenario were identified using BWM by three hypothetical decision-makers (the first three authors)[1] and then normalized, and final criteria weights were obtained by averaging. Table 5 lists the weights of

1 See Supplementary Tables 3–6.

Table 5 The weights of criteria for each scenario. Weights always sum to 1.0 and consistency ratios (CRs) are consistently below 0.25

	DM1	DM2	DM3	Average	Rank		DM1	DM2	DM3	Average	Rank
Economic cost scenario						*Social impact scenario*					
C1	0.0778	0.0769	0.3433	0.1660	2	C1	0.1901	0.3095	0.2204	0.2400	1
C2	0.3388	0.4330	0.2090	0.3269	1	C2	0.1901	0.1897	0.3354	0.2384	2
C3	0.1297	0.0897	0.0697	0.0964	4	C3	0.0634	0.0266	0.1102	0.0667	6
C4	0.0320	0.1794	0.0299	0.0804	7	C4	0.0951	0.0632	0.0256	0.0613	7
C5	0.1946	0.1076	0.1393	0.1472	3	C5	0.0760	0.1265	0.0882	0.0969	4
C6	0.1297	0.0364	0.1045	0.0902	6	C6	0.0355	0.0948	0.0735	0.0679	5
C7	0.0973	0.0769	0.1045	0.0929	5	C7	0.3498	0.1897	0.1469	0.2288	3
Sum	1	1	1	1		Sum	1	1	1	1	
CR	0.05	0.11	0.07	0.08		CR	0.03	0.07	0.11	0.07	
Environmentalist scenario						*Developer profits scenario*					
C1	0.1203	0.0572	0.1632	0.1136	4	C1	0.1863	0.1949	0.1992	0.1935	2
C2	0.1804	0.3848	0.1632	0.2428	1	C2	0.3186	0.3353	0.1328	0.2622	1
C3	0.0601	0.1526	0.0326	0.0818	6	C3	0.1242	0.0312	0.0285	0.0613	6
C4	0.3228	0.2290	0.0979	0.2165	2	C4	0.0294	0.0487	0.0797	0.0526	7
C5	0.1203	0.0654	0.0816	0.0891	5	C5	0.1242	0.0975	0.3273	0.1830	3
C6	0.0316	0.0763	0.0699	0.0593	7	C6	0.0931	0.0975	0.0996	0.0967	5
C7	0.1646	0.0346	0.3916	0.1969	3	C7	0.1242	0.1949	0.1328	0.1506	4
Sum	1	1	1	1		Sum	1	1	1	1	
CR	0.04	0.07	0.1	0.07		CR	0.05	0.05	0.07	0.06	

criteria that were generated according to different scenarios. All consistency ratios are less than 0.12 (dramatically lower than the 0.25 threshold cited in Gómez-Limón et al. (2020)), indicating that each decision-maker followed a consistent preference when ranking against best and worst criteria. The *estimated biomass energy* (C2) criterion ranks first in three of the four scenarios and second in the fourth scenario. This means that the potential biomass energy yield is considered by most decision-makers in this exercise to considerably affect the productivity of facilities, even among different scenarios. Another criterion is *population density* (C1) that ranks first in the social impact scenario and second in the economic cost and developer profits scenarios. This implies that the magnitude of demand for biomass energy plays an important role in several agendas.

The economic cost scenario is defined by the respective ranking of *estimated biomass energy* (C2), *population density* (C1), *proximity to road network* (C5), and *slope* (C3), which balances among costs. In the social impact scenario, the *population density* (C1), *estimated biomass energy* (C2), and *proximity to settlement area* (C7) have almost the same weight as the first three criteria, and the scenario attaches importance to social benefit. In contrast, the environmentalist scenario prioritizes conservation of the environment using criteria including *proximity to a water body* (C4) and *proximity to settlement area* (C7) in addition to the *estimated biomass energy* (C2). And fourth, the developer profits scenario emphasizes *proximity to road network* (C5) and *proximity to settlement area* (C7) along with *estimated biomass energy* (C2) and *population density* (C1) to prioritize productivity and efficiency.

The location suitability indexes with reference to different scenarios are mapped in Fig. 7. The general pattern is similar among scenarios, with highest suitability pixels situated around Ankara and Konya. Some visible differences are apparent in the southeast near Sanliurfa, where the developer profits scenario shows fewer high suitability pixels than other scenarios, while the social impacts scenario shows more high suitability pixels in this area.

As can be seen from Fig. 7, the four scenarios do not show considerable differentiation in the suitability results. One likely reason is that the *population density* (C1) and *estimated biomass energy* (C2) criteria rank first or second in all scenarios. Another reason may be that the *proximity to road network* (C5) and *proximity to settlement area* (C7) rank third or fourth in three scenarios, respectively. It is important to note that the results in this study show low sensitivity for changing criteria weights. The stability of results under all four scenarios implies that the suitability of chosen locations is robust, with respect to these specific criteria.

Figure 8 shows the comparison of relative coverage for each suitability class in each scenario. As in the first experiment, the moderately suitable class has the highest coverage and the two extreme classes (high suitability and unsuitability) show the lowest coverage, in all scenarios. Coverage appears to be least balanced, however, in the social impact and environmentalist scenarios, as both show proportionately fewer less suitable pixels than do the economic cost

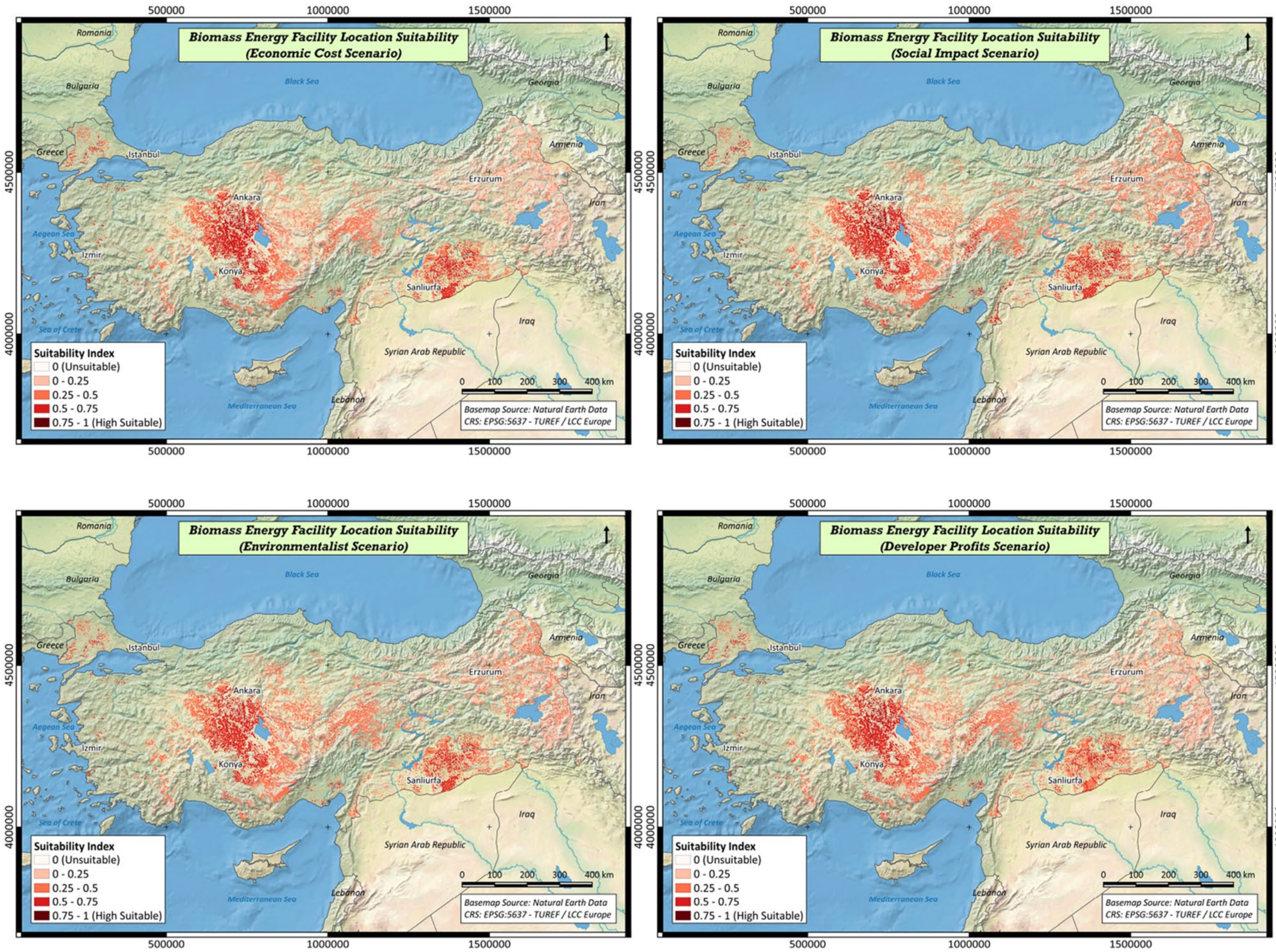
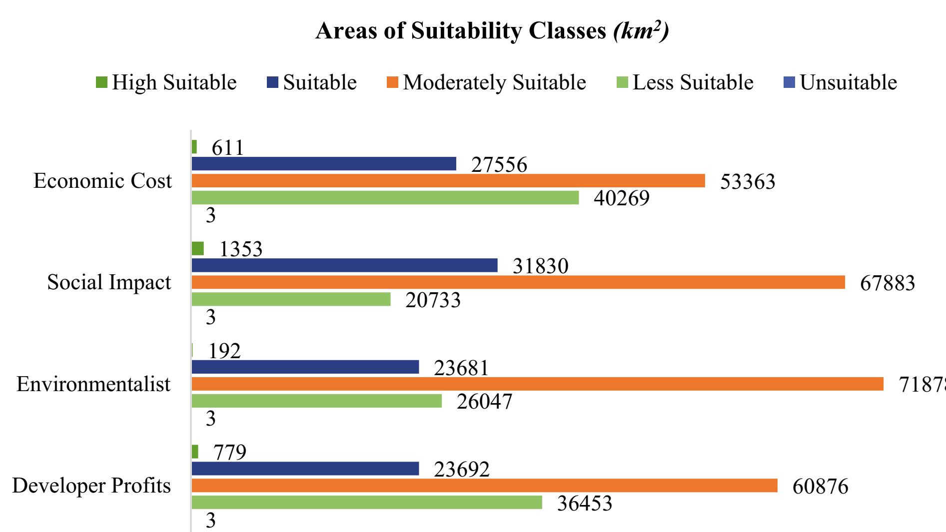


Fig. 7 The maps of location suitability according to four different scenarios

Fig. 8 The relative coverage of suitability classes according to different scenarios



or developer profits scenarios. The social impact scenario classifies the highest number of pixels as suitable or highly suitable. This shows that relative suitability of locations can differ when specific agendas (scenarios) are taken into account.

Discussion and prospects for future work

This paper finds suitable locations for biomass facilities using an integrated approach that integrates several methods including MCDM, GIS, BWM, and fuzzy logic. The analysis differs from previously published work in being applied to the whole of Turkey. The use of open-source tools and data supports both the accessibility of study methods and the replicability of the results. Another strong point of the study lies in obtaining results by merging different criteria sets established by a triad of decision-makers. This approach enables highly flexible decision making. Additionally, the sensitivity analyses take various scenarios into consideration; thus, the comprehensive suitability modeling results can be provided to administrative organizations for involving stakeholders with diverse or even divergent viewpoints and still developing efficient and feasible policies. In this connection, directives, policies, and regulations relating to the selection of biomass energy facility location are of great importance, because jurisdictions can incorporate idiosyncrasies that are germane to the locale but can nonetheless impact the selection of significant factors for location selection.

Renewable energy demands continue to increase in both Turkey and the world. The paper implements a methodology to select suitable locations of biomass facilities in large regions so as to efficiently benefit from energy potentials locally and nationally. The results of this study could guide discussions on prospective policies as well as spatial planning decisions related to biomass energy in other geographic regions and economic conditions across the globe. Furthermore, the study outcomes can help efforts in Turkey that aim to reach and exceed the objectives of the EU with respect to increasing the usage of renewable energy resources (Scarlat et al. 2019).

One important limitation of the study is that the weights of criteria were not determined according to a large number of experts from different sectors such as energy, transportation, and environment, and future work can concentrate on this issue. A second possible limitation is that this study was conducted at a 100-m spatial resolution. Other studies that address biomass facility location in smaller, more localized regions might warrant finer resolution, which could highlight local constraints that remain latent in this study. A finer resolution study could show anomalies in the criteria or constraints that are not evident in national-level results. In addition, the *proximity to a power grid connection* can be used as a criterion that represents the demand for energy facilities and embodies the *population density* criterion in future studies. Future work might consider the *proximity to groundwater* alongside water bodies. Another possible limitation of this study stems from not differentiating the bioenergy pathways, e.g., biofuel and biopower. For example, in a region exhibiting a higher demand for biopower than biofuels, wet biomass might not provide the most suitable source for biopower generation. Regional bioenergy that fits the demand of the geographical region is of vital importance for the most effective renewable energy transition. Considering that the relative suitabilities of different biomass types for bioenergy pathways notably differ across expansive regions such as Turkey, it will be beneficial in future studies to prioritize biomass types that fit localized bioenergy potential, in the context of sustainable supply chain management.

This research provides an applicable workflow for site selection of biomass energy facilities. The findings have important implications for deciding where to build new bioenergy facilities, and doing so in a manner that can be replicated in wide-ranging local and regional study areas. This research demonstrates the importance of encouraging stakeholders to participate in the decision-making process and shows that with robustly chosen criteria, one particular agenda will not unnecessarily bias final outcomes. Indeed, one finding of this work is that multiple and possibly incompatible agendas can produce similar site selection outcomes. The results of this study also suggest that a multifaceted approach consisting of open-source GIS, BWM, and fuzzy logic can guide precise investments with regard to bioenergy planning. The proposed approach could also be applied to decision-making problems related to other renewable energy sources such as solar and wind.

Turkey is obviously a landscape with highly varied terrain, population density, settlement patterns, and a balance between urban and agrarian economies. The characteristics of other study areas might affect the selection of constraints or the relative coverage of suitability classes. For example, some study areas might warrant additional constraints in terms of environmental impact, for example, natural heritage regions. Alternatively, areas lacking reliable road or rail networks might warrant selection of different proximity criteria.

Nonetheless, the objective of this paper to demonstrate the interplay of open-source GIS, fuzzy logic, and BWM for effective suitability modeling has offered valuable insights into the renewable energy situation in Turkey, as well as obtaining results that concur with the published literature. Future work will continue to explore the methods and the problem of biomass facility siting problems.

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References

Abdul Malek ABM, Hasanuzzaman M, Rahim NA (2020) Prospects, progress, challenges and policies for clean power generation from biomass resources. Clean Technol Environ Policy 22:1229–1253. https://doi.org/10.1007/s10098-020-01873-4

Avcıoğlu AO, Dayıoğlu MA, Türker U (2019) Assessment of the energy potential of agricultural biomass residues in Turkey. Renew Energy 138:610–619. https://doi.org/10.1016/j.renene.2019.01.053

Aydin F, Sarptas H (2020) Spatial assessment of site suitability for solar desalination plants: a case study of the coastal regions of Turkey. Clean Technol Environ Policy 22:309–323. https://doi.org/10.1007/s10098-019-01783-0

Babalola M (2018) Application of GIS-based multi-criteria decision technique in exploration of suitable site options for anaerobic digestion of food and biodegradable waste in Oita City. Japan Environ 5:77. https://doi.org/10.3390/environments5070077

Barzehkar M, Parnell KE, Mobarghaee Dinan N, Brodie G (2020) Decision support tools for wind and solar farm site selection in Isfahan Province. Iran Clean Technol Environ Policy 23:1–17. https://doi.org/10.1007/s10098-020-01978-w

Bojesen M, Boerboom L, Skov-Petersen H (2015) Towards a sustainable capacity expansion of the Danish biogas sector. Land Use Policy 42:264–277. https://doi.org/10.1016/j.landusepol.2014.07.022

BP (2020) Energy Outlook. https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/energy-outlook/bp-energy-outlook-2020.pdf

Cebi S, Ilbahar E, Atasoy A (2016) A fuzzy information axiom based method to determine the optimal location for a biomass power plant: a case study in Aegean Region of Turkey. Energy 116:894–907. https://doi.org/10.1016/j.energy.2016.10.024

Center for International Earth Science Information Network—CIESIN and Information Technology Outreach Services—ITOS (2013) Global Roads Open Access Data Set, Version 1 (gROADSv1). https://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1

Chukwuma EC, Okey-Onyesolu FC, Ani KA, Nwanna EC (2021) GIS bio-waste assessment and suitability analysis for biogas power plant: a case study of Anambra state of Nigeria. Renewable Energy 163:1182–1194. https://doi.org/10.1016/j.renene.2020.09.046

Costa FR, Ribeiro CAAS, Marcatti GE et al (2020) GIS applied to location of bioenergy plants in tropical agricultural areas. Renew Energy 153:911–918. https://doi.org/10.1016/j.renene.2020.01.050

Davtalab M, Alesheikh AA (2018) Spatial optimization of biomass power plant site using fuzzy analytic network process. Clean Technol Environ Policy 20:1033–1046. https://doi.org/10.1007/s10098-018-1531-5

Díaz-Cuevas P, Biberacher M, Domínguez-Bravo J, Schardinger I (2018) Developing a wind energy potential map on a regional scale using GIS and multi-criteria decision methods: the case of Cadiz (south of Spain). Clean Technol Environ Policy 20:1167–1183. https://doi.org/10.1007/s10098-018-1539-x

Díaz-Cuevas P, Domínguez-Bravo J, Prieto-Campos A (2019) Integrating MCDM and GIS for renewable energy spatial models: assessing the individual and combined potential for wind, solar and biomass energy in Southern Spain. Clean Technol Environ Policy 21:1855–1869. https://doi.org/10.1007/s10098-019-01754-5

Díaz-Vázquez D, Alvarado-Cummings SC, Meza-Rodríguez D et al (2020) Evaluation of biogas potential from livestock manures and multicriteria site selection for centralized anaerobic digester systems: the case of Jalisco, México. Sustainability 12:3527. https://doi.org/10.3390/su12093527

DoE (U.S. Department of Energy) (2020) Biomass Feedstocks. https://www.energy.gov/eere/bioenergy/biomass-feedstocks

EIA (U.S. Energy Information Administration) (2019) International Energy Outlook 2019. https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf

EUC (2016) European Union Copernicus, European Digital Elevation Model (EU-DEM). https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1?tab=download

EUC (2019a) European Union Copernicus, Corine Land Cover (CLC) 2018, Version 20. https://land.copernicus.eu/pan-european/corine-land-cover/clc2018?tab=download

EUC (2019b) European Union Copernicus, ESM. https://land.copernicus.eu/pan-european/GHSL/european-settlement-map/esm-2015-release-2019

EUC (2018) European Union Copernicus, High resolution layer: tree cover density (TCD) 2015. https://land.copernicus.eu/pan-european/high-resolution-layers/forests/tree-cover-density/status-maps/2015?tab=download

Famoso F, Prestipino M, Brusca S, Galvagno A (2020) Designing sustainable bioenergy from residual biomass: Site allocation criteria and energy/exergy performance indicators. Appl Energy 274:115315. https://doi.org/10.1016/j.apenergy.2020.115315

Franco C, Bojesen M, Hougaard JL, Nielsen K (2015) A fuzzy approach to a multiple criteria and Geographical Information System for decision support on suitable locations for biogas plants. Appl Energy 140:304–315. https://doi.org/10.1016/j.apenergy.2014.11.060

GDAL/OGR Contributors (2021) GDAL/OGR Geospatial Data Abstraction Software Library. Open Source Geospatial Foundation. https://gdal.org/

Gital Durmaz Y, Bilgen B (2020) Multi-objective optimization of sustainable biomass supply chain network design. Appl Energy 272:115259. https://doi.org/10.1016/j.apenergy.2020.115259

Gómez-Limón J, Arriaza M, Guerrero-Baena M (2020) Building a composite indicator to measure environmental sustainability using alternative weighting methods. Sustainability 12:4398. https://doi.org/10.3390/su12114398

GRASS Development Team (2021) GRASS GIS. https://grass.osgeo.org/

Guerini Filho M, Steinmetz RLR, Bezama A et al (2019) Biomass availability assessment for biogas or methane production in Rio

Grande do Sul, Brazil. Clean Technol Environ Policy 21:1353–1366. https://doi.org/10.1007/s10098-019-01710-3

Guler D, Charisoulis G, Buttenfield B, Yomralioglu T (2021) QGIS spatial fuzzification. https://github.com/gulerdo/spatial-fuzzification

Guler D, Yomralioglu T (2021) Bicycle station and lane location selection using open source GIS technology. In: Mobasheri A (ed) Open source geospatial science for urban studies: the value of open geospatial data. Springer, Cham, pp 9–36

Hofmann P (2016) Defuzzification strategies for fuzzy classifications of remote sensing data. Remote Sens 8:467. https://doi.org/10.3390/rs8060467

IEA (International Energy Agency) (2018) World Energy Outlook 2018. https://www.iea.org/reports/world-energy-outlook-2018

Igliński B, Piechota G, Buczkowski R (2015) Development of biomass in polish energy sector: an overview. Clean Technol Environ Policy 17:317–329. https://doi.org/10.1007/s10098-014-0820-x

IOPRT (2021) The Investment Office of the Presidency of the Republic of Turkey, Energy. https://www.invest.gov.tr/en/sectors/pages/energy.aspx

Jayarathna L, Kent G, O'Hara I, Hobson P (2020) A geographical information system based framework to identify optimal location and size of biomass energy plants using single or multiple biomass types. Appl Energy 275:115398. https://doi.org/10.1016/j.apenergy.2020.115398

Jeong J, Ramírez-Gómez Á, Jeong JS, Ramírez-Gómez Á (2017) A multicriteria GIS-based assessment to optimize biomass facility sites with parallel environment—a case study in Spain. Energies 10:2095. https://doi.org/10.3390/en10122095

Kedron P, Li W, Fotheringham S, Goodchild M (2020) Reproducibility and replicability: opportunities and challenges for geospatial research. Int J Geogr Inf Sci 35:1–19. https://doi.org/10.1080/13658816.2020.1802032

Kheybari S, Kazemi M, Rezaei J (2019) Bioethanol facility location selection using best-worst method. Appl Energy 242:612–623. https://doi.org/10.1016/j.apenergy.2019.03.054

Latterini F, Stefanoni W, Suardi A et al (2020) A GIS approach to locate a small size biomass plant powered by olive pruning and to estimate supply chain costs. Energies 13:3385. https://doi.org/10.3390/en13133385

Li Z (2018) Study of site suitability assessment of regional wind resources development based on multi-criteria decision. Clean Technol Environ Policy 20:1147–1166. https://doi.org/10.1007/s10098-018-1538-y

MAFRT (2021) Ministry of Agriculture and Forestry of the Republic of Turkey, Data Portal. http://veri.tarimorman.gov.tr/

Masud MH, Ananno AA, Arefin AME et al (2019) Perspective of biomass energy conversion in Bangladesh. Clean Technol Environ Policy 21:719–731

Melikoglu M (2017) Vision 2023: Status quo and future of biomass and coal for sustainable energy generation in Turkey. Renew Sustain Energy Rev 74:800–808. https://doi.org/10.1016/j.rser.2017.03.005

Melikoglu M, Menekse ZK (2020) Forecasting Turkey's cattle and sheep manure based biomethane potentials till 2026. Biomass Bioenerg 132:105440. https://doi.org/10.1016/j.biombioe.2019.105440

MENRRT (2014) Ministry of Energy and Natural Resources of the Republic of Turkey, Turkey Biomass Energy Potential Atlas. https://bepa.enerji.gov.tr/

Mi X, Tang M, Liao H et al (2019) The state-of-the-art survey on integrations and applications of the best worst method in decision making: Why, what, what for and what's next? Omega (united Kingdom) 87:205–225. https://doi.org/10.1016/j.omega.2019.01.009

Morato T, Vaezi M, Kumar A (2019) Developing a framework to optimally locate biomass collection points to improve the biomass-based energy facilities locating procedure—a case study for Bolivia. Renew Sustain Energy Rev 107:183–199. https://doi.org/10.1016/j.rser.2019.03.004

MTIRT (2021) Ministry of Transport and Infrastructure of the Republic of Turkey, Airports. https://www.dhmi.gov.tr/Sayfalar/EN/DefaultEN.aspx

OSM Contributors (2021) Openstreetmap. https://download.geofabrik.de/

PRT (2019) The Presidency of the Republic of Turkey, Eleventh Development Plan (2019–2023). http://www.sbb.gov.tr/wp-content/uploads/2020/03/On_BirinciPLan_ingilizce_SonBaski.pdf

QGIS Development Team (2021) QGIS. https://qgis.org/en/site/

REN21 (2020) Renewables 2020 Global Status Report. https://www.ren21.net/wp-content/uploads/2019/05/gsr_2020_full_report_en.pdf

Rezaei J (2016) Best-worst multi-criteria decision-making method: some properties and a linear model. Omega 64:126–130. https://doi.org/10.1016/j.omega.2015.12.001

Rezaei J (2015) Best-worst multi-criteria decision-making method. Omega 53:49–57. https://doi.org/10.1016/j.omega.2014.11.009

Rodríguez R, Gauthier-Maradei P, Escalante H (2017) Fuzzy spatial decision tool to rank suitable sites for allocation of bioenergy plants based on crop residue. Biomass Bioenerg 100:17–30. https://doi.org/10.1016/j.biombioe.2017.03.007

SAGA Development Team (2021) SAGA. http://www.saga-gis.org/en/index.html

Sahoo K, Mani S, Das L, Bettinger P (2018) GIS-based assessment of sustainable crop residues for optimal siting of biogas plants. Biomass Bioenerg 110:63–74. https://doi.org/10.1016/j.biombioe.2018.01.006

Scarlat N, Fahl F, Lugato E et al (2019) Integrated and spatially explicit assessment of sustainable crop residues potential in Europe. Biomass Bioenerg 122:257–269. https://doi.org/10.1016/j.biombioe.2019.01.021

Settou B, Settou N, Gouareh A et al (2020) A high-resolution geographic information system-analytical hierarchy process-based method for solar PV power plant site selection: a case study Algeria. Clean Technol Environ Policy 1:3. https://doi.org/10.1007/s10098-020-01971-3

Silva S, Alçada-Almeida L, Dias LC (2017) Multiobjective programming for sizing and locating biogas plants: a model and an application in a region of Portugal. Comput Oper Res 83:189–198. https://doi.org/10.1016/j.cor.2017.02.016

Toklu E (2017) Biomass energy potential and utilization in Turkey. Renewable Energy 107:235–244. https://doi.org/10.1016/j.renene.2017.02.008

TurkStat (2020) Environment and Energy. https://data.tuik.gov.tr/Kategori/GetKategori?p=Cevre-ve-Enerji-103

TurkStat (2019) Population and Demography. https://data.tuik.gov.tr/Kategori/GetKategori?p=Population-and-Demography-109

Uyan M (2017) Optimal site selection for solar power plants using multi-criteria evaluation: a case study from the Ayranci region in Karaman, Turkey. Clean Technol Environ Policy 19:2231–2244. https://doi.org/10.1007/s10098-017-1405-2

Van Holsbeeck S, Srivastava SK (2020) Feasibility of locating biomass-to-bioenergy conversion facilities using spatial information technologies: a case study on forest biomass in Queensland. Australia Biomass and Bioenergy 139:105620. https://doi.org/10.1016/j.biombioe.2020.105620

WEC (2016) World Energy Council, World Energy Resources. http://www.wec-france.org/DocumentsPDF/Etudes_CME/World-Energy-Resources_SummaryReport_2016.pdf

Woo H, Acuna M, Moroni M et al (2018) Optimizing the location of biomass energy facilities by integrating multi-criteria analysis

(MCA) and geographical information systems (GIS). Forests 9:585. https://doi.org/10.3390/f9100585

Wu Y, Yan Y, Wang S et al (2019) Study on location decision framework of agroforestry biomass cogeneration project: a case of China. Biomass Bioenerg 127:105289. https://doi.org/10.1016/j.biombioe.2019.105289

Yalcinkaya S (2020) A spatial modeling approach for siting, sizing and economic assessment of centralized biogas plants in organic waste management. J Clean Prod 255:120040. https://doi.org/10.1016/j.jclepro.2020.120040

Yücenur GN, Çaylak Ş, Gönül G, Postalcıoğlu M (2020) An integrated solution with SWARA&COPRAS methods in renewable energy production: city selection for biogas facility. Renew Energy 145:2587–2597. https://doi.org/10.1016/j.renene.2019.08.011

Yuruk F, Erdogmus P (2018) Finding an optimum location for biogas plant: a case study for Duzce, Turkey. Neural Comput Appl 29:157–165. https://doi.org/10.1007/s00521-016-2424-3

Zadeh LA (1997) Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic. Fuzzy Sets Syst 90:111–127. https://doi.org/10.1016/S0165-0114(97)00077-8

Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zareei S (2018) Evaluation of biogas potential from livestock manures and rural wastes using GIS in Iran. Renew Energy 118:351–356. https://doi.org/10.1016/J.RENENE.2017.11.026

Zheng Y, Qiu F (2020) Biomass and Bioenergy Bioenergy in the Canadian Prairies: assessment of accessible biomass from agricultural crop residues and identification of potential biorefinery sites. Biomass Bioenerg 140:105669. https://doi.org/10.1016/j.biombioe.2020.105669

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