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ASTRONOMICAL OBSERVATORY SITE SELECTION USING FUZZY AHP AND BWM METHODS

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SUMMARY: Establishing an observatory often involves complex decisions, such as choosing a site based on multiple conflicting criteria. In this study, we develop a multi-criteria decision analysis process by combining Geographic Information System (GIS) analysis with the (MCDA) Multi-Criteria Decision Analysis and use this process to determine the most suitable sites for the construction of an observatory in the Malatya urban area. GIS was used to calculate, classify, and analyze criteria, while FAHP (Fuzzy Analytic Hierarchy Processes, Buckley's method) and BWM (MCDA type Best-Worst Method) methods were used to weight the decision criteria and determine their effects on alternative sites. While the Cloud Cover criterion in the BWM method was the most important criterion with 28%, the most important criterion for the FAHP method had a comparable value of 27.8%. Meteorological criteria were the most important criteria group with values of 50.4% according to the FAHP method and 44.6% according to the BWM method. The study is based on meteorological, geographic, and anthropogenic datasets, suggesting the most appropriate sites for the astronomical observatory within the boundaries of the study area. The proposed sites are the result of site selection, which is the first phase of site selection for astronomical observatories. This site selection is important to limit the number of field alternatives. It is necessary to conduct field tests among the proposed areas and select the final site according to the results. The successful use of GIS and more than one MCDA method will pave the way for the development of various methods for astronomical observatory site determination.

Key words. Atmospheric effects – Instrumentation: miscellaneouss – Light pollution

1. INTRODUCTION

To maximize observatory efficiency, ideal sites should be identified, especially with respect to meteorological data sets. Site selection is the process of determining the most ideal site by using many data sets consisting of two phases, site selection, and field test phase (Hudson and Simstad 2010, Koc-San et al. 2013). The field test phase is a process that includes phases such as sky brightness, atmospheric visibility, precipitable water vapor, and atmospheric extinction coefficient calculation, and should be conducted at the site of each alternative candidate area (Koc-San et al. 2013). This process will prolong as the number of alternatives increases, causing not only time but also energy and cost loss (Yılmaz 2023). For these reasons, it is inevitable to reduce the number of alternatives by conducting a site selection study before the field test. The use of geographic information systems (GIS) and multi-criteria decision analysis (MCDA) provides an efficient method for site selection studies because the problem can be easily modeled, it is compatible with statistical methods, data from many sources can be managed, and the evaluation of the results is simple (Koc-San et al. 2013, Yılmaz 2023, Kumi-Boateng et al. 2021, Nikolić et al. 2023, Pileggi 2019). Fuzzy AHP (FAHP) preserves the advantages and conveniences offered by AHP, especially in the relative evaluation of multiple data in qualitative and quantitative terms, and provides a hierarchical procedure like AHP. It facilitates benchmarking and pairwise comparisons, improves consistency, creates priority vectors, and reflects expert insights (Kahraman et al. 2004). These features have led to the FAHP method being chosen by researchers in many studies. There are several studies in the literature that combine GIS, FAHP, and MCDA methods: Site selection for optimal wind farms using FAHP and GIS (Liu et al. 2020), Site selection for municipal solid waste landfills based on FAHP and GIS in the Asir region of Saudi Arabia (Mallick 2021). FAHP and GIS were used to determine cloud cover and water-related locations of plant seeds on the map (Valjarević et al. 2022). Groundwater quality modeling and evaluation was done using GIS, FAHP method (Aslan 2023). One of the MCDA methods is BWM (best-worst method). This method presented by Rezaei (2015) is another new powerful and consistent MCDA method used to determine the criteria weights Rahimi et al. (2020), Mi et al. (2019). Although the BWM method is new, it has been preferred in many studies because it produces results with fewer pairwise comparisons compared to other MCDA methods, simplifies the steps of mathematical operations due to the use of only integers, and has a high percentage of consistency (Pamučar et al. 2017). BWM is one of the methods used in the study in which the alternatives for engine oil were evaluated using different methods (Volkan et al. 2022). In a study on sustainable evaluation of technology selection for municipal sewage sludge treatment, the BWM method was used to determine the criteria weights (Ren et al. 2017). In the study on circular economy and sustainability in eco-industrial parks, the analyzes were performed using the BWM method (Zhao et al. 2018). The FAHP and BWM methods are used to determine the importance of criteria for observatory site selection, and efforts are made to rank and analyze the criteria using different methods by creating separate result maps for each method.

İnönü University Observatory was officially opened on May 18, 2012 under, the leadership of Dr. Tuncay Özdemir within the boundaries of İnönü University in Malatya Province (Özdemir 2012). While the population of the province was 762.366 in 2012, it will be 814.386 in 2023. The population growth of the city leads to an increase of lights in the city. Meanwhile, the growth of the university and the construction of new teaching buildings have led to an increase in anthropogenic impacts around the observatory. These developments threaten the future of the observatory. These reasons lead us to propose new locations for optical astronomical observation that will improve the quality of astronomical observations. The objective of our study is to propose the best alternative sites geographically, meteorologically, and anthropogenically within the provincial boundaries. The parameters used to determine the most suitable location for the astronomical observatories in our study were taken from the works of Walker (1984), Cowles (1989), Hudson and Simstad (2010), Koc-San et al. (2013). Similar studies to our study were conducted by D. Koc-San et al. (Koc-San et al. 2013) for Antalya province and by the author of this study for Erzincan province (Yılmaz 2023). Although different criteria were used in the studies, the criteria weights were determined by the AHP method. In 2015, another study entitled "Astronomical Site Selection for Turkey" was conducted using the techniques of GIS. The criteria used in this study and the method used to determine the criteria weights are different from our study (Aksaker et al. 2015).

Our study is based on 3 main parameters: meteorological, geographical, and anthropogenic. In conjunction with these main parameters, 9 criteria were established. Each created criterion is represented by a raster data layer in the program GIS (Koc-San et al. 2013). The weighting values of each data layer were determined by the experts as a result of a pairwise comparison of the criteria with each other. This method of determining the weights is one of the steps of the FAHP, and BWM methods. In our study, we propose the areas where the optical astronomical observatory will operate with maximum efficiency. It is the data resulting from the weighting of the maps obtained by digitizing the results of the data analysis using remote sensing, BWM and FAHP methods in the system GIS. As far as we know, our study is the first to select an observation site using the FAHP and BWM methods. The data obtained to establish the criteria and those used in the studies to determine the appropriate site for the observatory are reliable. The successful application of the GIS, FAHP and BWM methods of these data in many studies, as we have exemplified above, made it inevitable that the selection of a suitable site for the observatory would be carried out using a similar methodology and be successful. Successful application of this methodology to observation site selection studies will yield satisfactory results.

2. WORKSPACE AND DATA USED

The study area is located in the Upper Euphrates Basin in the Eastern Anatolia region of Malatya Province, Turkey, and covers 12 313 km^2. It is located between 35° 54′ and 39° 03′ north latitude and 38° 45′ and 39° 08′ east longitude (Fig. 1). Malatya province has 77 cloudy days, 152 partly cloudy days, and 136 cloudless days in the annual average (Toprak 2013). Continental climatic conditions prevail in the study area and summer months are hot. The winter season is quite cold due to high pressure in Siberia. The annual average temperature in Malatya is 13.7 °C (Bayindir 2006). On average, there are 77 cloudy or hazy days, 152 partly cloudy days, and 136 clear days in the study area (Toprak 2013). From these annual average days, it can be concluded that observations can be carried out fully or partially in about two-thirds of the year. Areas at high altitude, and without humidity are the most suitable for the construction of observatories (Koc-San et al. 2013). About 45% of the borders of Malatya province consist of mountains. It contains many mountains and hills, the highest of which is Beydağları with an altitude of 2545 m (Engin and Şengün 2016).

In our study, details of the data sets used to determine the most suitable location for astronomical observing conditions: will be explained in detail. The data used in the study and the sources from which it was obtained can be seen in Table 1).

2.1. Meteorological datasets

In our study, the meteorological data set includes the criteria of Cloud Cover, Precipitable Water Vapor, and Wind Speed. One of the most important criteria that negatively affects astronomical observatories is the cloud cover of the study area, and another criterion that negatively affects atmospheric permeability is the amount of collapsing water (Yin et al. 2012, Koc-San et al. 2013).

MODIS VIS provides data with a resolution of 250 m (2 bands) and SWIR of 500 m (5 bands), (Barnes et al. 1998). The overall absolute accuracy of MOD10A1/MOD35L2 and MOD05L2 is about 93%, which is satisfactory (Hall and Riggs 2007). In our study, MOD10A1 products from the National Snow and Ice Data Center (NSIDC) and MOD05L2 products from the Atmosphere Archive and Distribution System (LAADS) were used for the Cloud Cover dataset and the Precipitable Water dataset, respectively. The grains of MOD10A1/MYD10A1 have the shape of a sine wave and the side length is over 1000 km. MOD10A1 presents fractional snow cover data, snow, cloud mask, terrain and water data as a thematic map with HDF enhancement (Hall and Riggs 2007). MODIS cloud mask data are used about the presence or absence of the cloud (Strabala 2005). These data were obtained from the fractional snow cover layer of MOD10A1/MOD35L2, (Hall and Riggs 2007). Another important criterion in meteorological datasets is the Precipitable Water Vapor. The amount of collapsible water is one of the important parameters that negatively affect atmospheric permeability. Advanced Very High-Resolution Radiometer (AVHRR) sensors are a suitable system for indicating water vapor content (Sobrino et al. 2003), and MODIS (Gao and Goetz 1990, Kaufman and Gao 1992). To obtain the map of precipitable water vapor of the study area, the water vapor infrared datasets in HDF format obtained from the MOD05L2 (MYD05L2) product were used by (Sobrino et al. 2003, Kern et al. 2008). In our study, 1095 data (365 × 3 years) were used as a result of downloading more than four thousand granules containing the study area for each of the criteria Cloud Cover and Precipitable Water Vapor in HDF format and processing in the program GIS, this is a 3-year period from February 1, 2020 to February 28, 2023. The global wind atlas method developed by the Technical College of Denmark (DTU) Wind Energy and Vortex with support from the World Bank Group provides wind speed data. Wind speed data for the study area were taken from the Global Wind Atlas 3.2 maps, which is a web-based application. Version 3.2 of the GWA provides quality data at 10 m resolution. The GWA provides alternatives for mapping wind sources at 10, 50, 100, 150, and 200 m above the ground in the form of 250 m horizontal grids. Users can access the data free of charge from anywhere in the world. Evaporation is inversely proportional to the speed at which air flows over water. Therefore, increased wind speed decreases evaporation and humidity, which indirectly affects the selection of sites for astronomical observatories (Ravi and D'Odorico 2005).

2.2. Geographical datasets

The geographic dataset consists of four criteria: Digital Elevation Model (DEM), geology, landslides, and active fault lines. Sky transparency changes proportionally with elevation Hudson and Simstad (2010). For this reason, the Digital Elevation Model (DEM) is one of the most important criteria in our study. Shuttle Radar Topography Mission (SRTM) data obtained with the C-band interferometry instrument SAR on the space shuttle Endeavor were used (Effat et al. 2013). DEM data from USGS Earth Explorer saved in ArcGIS 10.8 (Mohammed and Sayl 2021). Construction sites should be located as far as possible from areas vulnerable to natural disasters. To create safe construction areas, our study used maps of landslide zones and active fault lines (Akbaş et al. 2011, Çan et al. 2013). One of the criteria used in suitable site selection studies is the landslide inventory data. The data were obtained from the landslide maps (1/25000) of the General Directorate of Mineral Research and Exploration (MTA). According to the landslide inventory maps, landslide activities can be classified as ancient landslides, active landslides, fracture-flow landslides, and so on. In the landslide map we created, all landslide activities were selected as areas unsuitable for construction. Another criterion we use is the active fault lines within the boundaries of the study area. The MTA active fault map was used as the data source. Malatya province is located in a region that can be classified as highly prone to earthquakes. It contains 3 important fault zones. These are the East Anatolian fault zone, which can produce devastating earthquakes in the south, the Sürgü fault in the southwest, and the Malatya fault zone in the continuation of the Sürgü fault (İrap 2021). MTA (1/25000) active fault maps were digitized with the GIS program and the active fault map of the study area was created.

2.3. Anthropogenic datasets

In our study, the anthropogenic datasets consist of the parameters of urban lighting, distance to roads, and distance to mining sites. People's need for light is undisputed. However, the increase in construction projects and artificial light sources near observatories makes city lighting one of the most important parameters negatively affecting astronomical observations.

The Earth Observation Group (EOG), which excels in nocturnal remote sensing (EOG) studies, produces high-quality global nighttime light maps using data from nighttime satellite observations. The Visible and Infrared Imaging Package (VIIRS), carried by the JPSS satellites, provides high-quality images in low-light conditions (Elvidge et al. 2021). EOG provides global, continental, and national nighttime light data at a resolution of 15 arcseconds (500m at the equator) to users free of charge. In our study, the EOG - VNL V2.1 Night Lights Time Series data set was used to determine the effect of city lights in selecting the appropriate site for the astronomical observatory. It is important that there are no mining areas near the observatories that cause continuous dust formation. Dust increases the cloudiness of the sky and negatively affects the observing conditions (Koc-San et al. 2013). The locations of the mining sites were obtained from the General Directorate of Mining Affairs of Turkey. When the observatory was built, the distance to the roads was set as a criterion to reduce transportation costs for building materials and to allow easy access to the observatory. The methodology of the study mainly includes data collection using remote sensing methods and government agencies, data analysis using BWM, FAHP methods and GIS applications, and visualization of the results in a GIS environment (Haklay and Weber 2008). Distance to roads criteria data was obtained from OpenStreetMap.

3. METHODOLOGY

To model the study of selecting suitable sites for astronomical observatory construction, the process of GIS-MCDA can be essentially described in four steps: Problem definition, criteria definition (Table 2) determination of criteria weights (using FAHP and BWM methods), and standardization, analysis of criteria and production of result maps and interpretation (see Table 6) (Nikolić et al. 2023, Malczewski and Rinner 2015, Domazetović et al. 2019a,b, Eastman 1999). To determine the weights of 9 criteria according to the FAHP and BWM models, the experts performed 36 comparisons (n.n-1/2) and 15 (2n-3) comparisons, respectively. After data analysis, the criteria weights are determined (Feizi et al. 2021, Wang et al. 2023) by both MCDA methods.

A model was created in Arc- GIS 10.8 software to enter the weights into the criteria maps. In this study, three main parameters consisting of anthropogenic, meteorological, and geographic data sets were used to select the appropriate location for the astronomical observatory (Koc-San et al. 2013, Yılmaz 2023).

A map was created in the environment GIS by obtaining the datasets of each criterion, drawing editor, remote sensing data, or digital maps, Yılmaz (2023). Each dataset represents a criterion layer. All criterion layers were converted to a vector format to allow input of fitness values. A common range was added to each level and assigned values between 1 and 5, with 5 representing the best fitness for astronomical observing conditions and 1 representing the worst fitness for astronomical observing conditions (Setiawan et al. 2004, Nuthammachot and Stratoulias 2021, Abdo et al. 2022, Nikolić et al. 2023). Using field data added to all criterion levels, the criterion maps were transformed from vector to raster maps. After these transformations, the raster maps for the FAHP method are defined as fuzzy membership in the GIS application (the fuzzy membership application provides standardization of the criteria in raster format based on GIS and assigns a value between 0 and 1 to each of the raster cells) (Bahrani et al. 2016, Gorsevski et al. 2012). After this step, the weights of the maps calculated with the FAHP method were entered with the application GIS -raster calculator (Ibrahim et al. 2011). In the last stage, the weighted maps were overlaid with the application GIS-Fuzzy Overlay, and the result map was created (Rahimi et al. 2020). When the result map was created according to the BWM criteria, the rescaled rater maps were weighted in the range of 1-5 and overlaid with the application GIS -Weighted overlay, and the result map was obtained (Yılmaz 2023). To our knowledge, this is the only study in which astronomical site selection was performed using the FAHP and BWM methods.

3.1. Processing of meteorological data sets

Over 4000 data were obtained from the MOD35L2 product, and the data were converted into a single layer using the New Mosaic Raster program in GIS, which was used as the Cloud Cover data of the study area (Wilson and Power 2018). It is well known that cloud cover complicates astronomical observing conditions. Therefore, the resulting layer data were rescaled (see Table 2). The Precipitable Water data were taken from the MOD05L2 dataset and rescaled in a final step by going through the same steps as for the Cloud Cover data (see Table 2). The scaling process took into account that rainfall data negatively affect astronomical observing conditions. Wind Speed data were obtained at the national boundaries using the Global Wind Atlas application and cropped according to the study area boundaries in the GIS program. The cropped map was rescaled and used as wind speed data (see Table 2). Astronomical visibility is affected by the fact that the wind, which

Table 1: Criteria resources table.

Code	Criteria	Source
C1	Distance To Road	OpenStreetMap
C2	Distance To Landslide	General Directorate Of Mineral Research And Exploration
C3	Distance To Active Faults	General Directorate Of Mineral Research And Exploration
C4	Wind Speed	Global Wind Atlas
C5	Mining Sites	General Directorate Of Mining Affairs Of Türkiye
C6	City Lights	Earth Observation Group (Eog)
C7	Precipitable Water Vapor	Modıs - Mod05l2/Myd05l2
C8	Cloud Cover	Modıs – Mod35l2
C9	Dem	Srtm

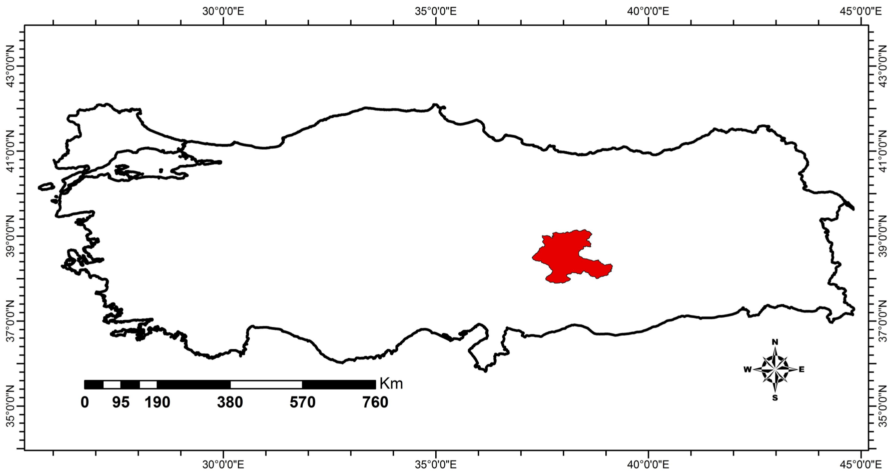

Fig. 1: Location of the work area.

forms at the height of the observatory, changes direction and causes turbulence due to contact with the surrounding geographic formations. In addition, when the wind speed exceeds 11 m/s, the stress on the telescope and dome causes vibrations (Liu et al. 2020). When the wind speed exceeds 11 m/s, it negatively affects the observation conditions (Solmaz et al. 2021) the wind speed in the recommended areas does not exceed this value.

3.2. Processing of geographic datasets

In the study, landslide and active fault maps of the study area were drawn by hand in JSON format using the "Drawing Editor" application, which is one of the geoscience map display programs of the Directorate General of Mineral Research and Exploration, and converted to KML format and transferred to GIS. All geospatial data were digitized and scaled in an environment of GIS (see Table 2). When creating the layers for landslides and active fault lines, these layer data were marked on the map and scaled according to the distances and close distances to the areas with landslides and active fault lines by using the buffer infrastructure of the GIS application (see Table 2) (Koc-San et al. 2013). Elevation data came from the GTOPO30 application and were scaled using the same procedures as the Wind Speed datasets (see Table 2). The scaling was based on the assumption that the atmosphere becomes clearer with increasing altitude, and altitude was assumed to have a positive effect on optical astronomical observing conditions.

3.3. Processing of anthropogenic datasets

City lights data were obtained by cropping from maps produced by the Visible and Infrared Imaging (VIIRS) packages on the JPSS satellites of the Earth Observation Group (EOG), which conducts nighttime remote sensing (EOG) studies corresponding to the boundaries of the study area, and presented at a resolution of 15 arcseconds (500m at the equator) was used (Baugh et al. 2013). City lights are one of the most important parameters that negatively affect astronomical observations. The raster data were scaled to account for the negative influence of city lights (see Table 2).

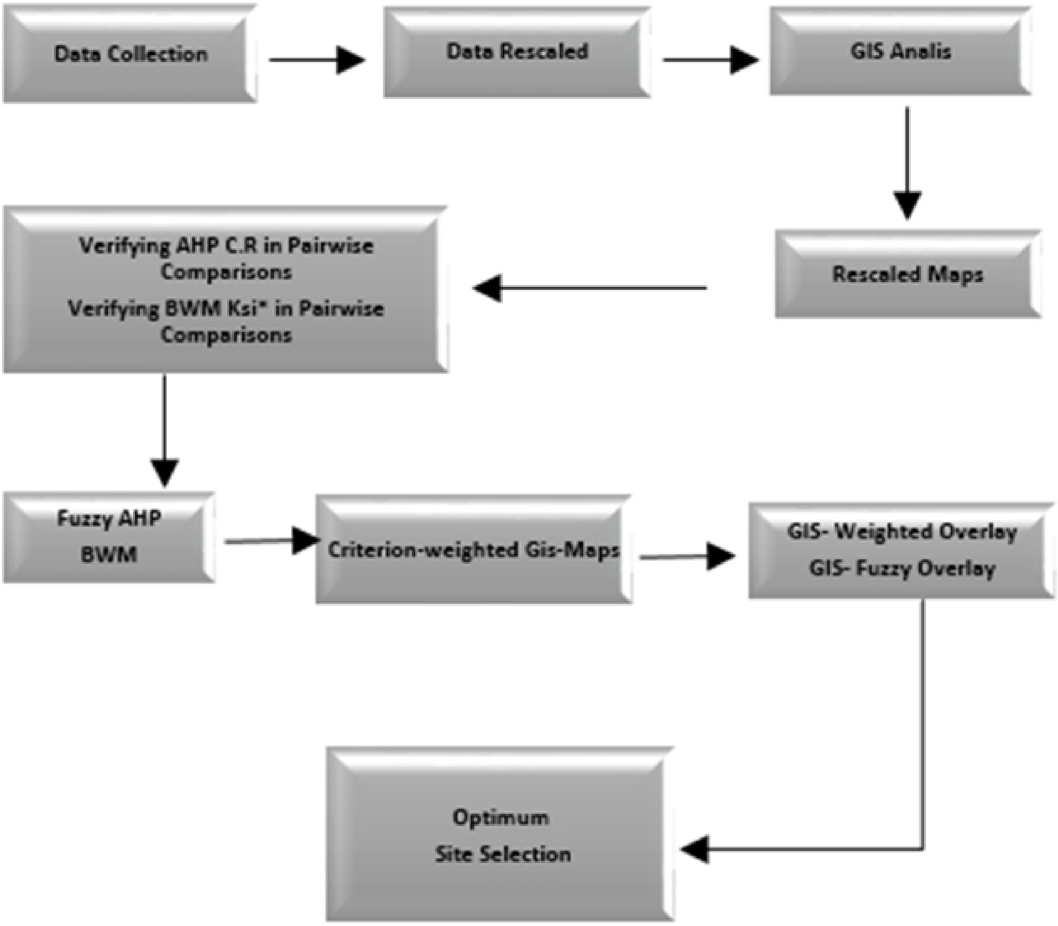

Fig. 2: Flow chart of the process steps followed in the study.

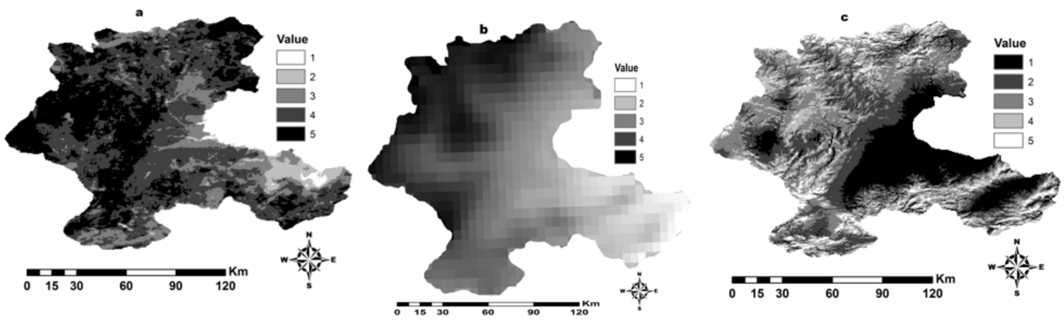

Fig. 3: The used meteorological data sets: Cloud Cover (a), Precipitable Water Vapor (b), Wind Speed (c).

There are metal mines (chromium, copper, iron, fluoride, copper-zinc-lead) in the study area. It contains minerals used as industrial raw materials (asbestos, cement raw materials, sand-gravel, gypsum, limestone, marble, profilite, thorium, vermiculite). This results in an excessive dust layer near mining facilities (Yılmaz 2023). Therefore, the scaling of the raster maps took into account the need to place the observatory buildings in areas far from the mine sites and scaled through a buffer analysis, (see Table 2).

Road data were obtained from the OpenStreetMap application. The obtained data are classified as distance with the GIS buffer infrastructure. These classes are scaled from near to far to allow a convenient access to the observatory building (see Table 2).

Table 2: Criteria and reclassification table.

	$x<2000$	1		$x<3{,}211$	5
Distance to active faults	$2000 \leqslant x<3000$	2		$3{,}211\leqslant x<11{,}36$	4
	$3000\leqslant x<4000$	3	City lights	$11{,}36\leqslant x<23{,}96$	3
	$4000\leqslant x<5000$	4		$23{,}96\leqslant x<43{,}72$	2
	$5000\leqslant x$	5		$43{,}72\leqslant x<63$	1
	$x<100$	1		$0{,}79\leqslant x<3{,}02$	1
	$100\leqslant x<200$	2		$3{,}02\leqslant x<4{,}28$	2
Landslide	$200\leqslant x<300$	3	Wind Speed	$4{,}28\leqslant x<5{,}4$	3
	$300\leqslant x<400$	4		$5{,}4\leqslant x<6{,}84$	4
	$400\leqslant x$	5		$6{,}84\leqslant x<12{,}66$	5
	$x<100$	5		$572\leqslant x<984$	1
	$100\leqslant x<200$	4		$984\leqslant x<1283$	2
Distance to roads	$200\leqslant x<300$	3	Dem	$1283\leqslant x<1558$	3
	$300\leqslant x<400$	2		$1558\leqslant x<1856$	4
	$400\leqslant x$	1		$1856\leqslant x<2522$	5
	$x<500$	1		$7{,}182<x<8{,}368$	5
	$500\leqslant x<1000$	2		$8{,}369<x<9{,}027$	4
Point density of mining sites	$1000\leqslant x<1500$	3	Precipitable Water Vapor	$9{,}028<x<9{,}073$	3
	$1500\leqslant x<2000$	4		$9{,}074<x<10{,}606$	2
	$2000\leqslant x$	5		$10{,}607<x<11{,}889$	1
	$-4117<x<-3111$	5			
	$-3111\leqslant x<-2429$	4			
Cloud Cover	$-2429\leqslant x<-1209$	3			
	$-1209\leqslant x<1015$	2			
	$1015\leqslant x<5036$	1			

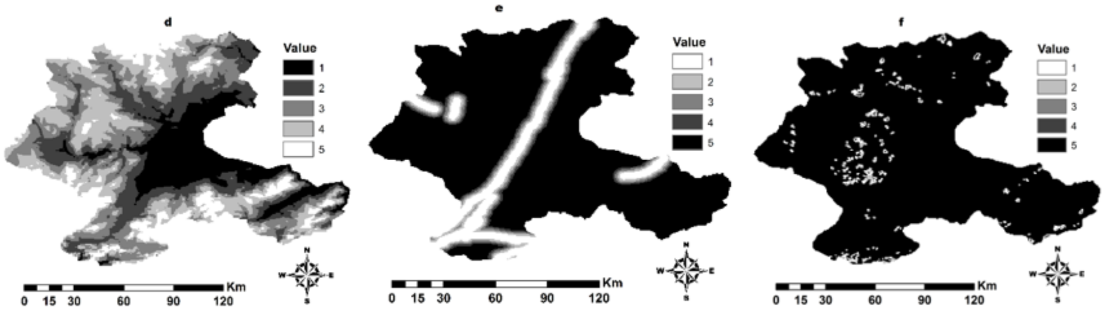

Fig. 4: The used geographical data: DEM (d), distance map of active fault lines (e), and landslide (f).

3.4. Analytic hierarchy process

Maps created for all criteria used in the study were scaled, with 1 representing negative effects on astronomical observing conditions and 5 representing positive contributions (Yılmaz 2023). Each scaled criteria map was overlaid in the program GIS according to the criteria weights determined by the FAHP method. The weight ratios determined by the FAHP method are one of the most important stages of the study. The FAHP (Fuzzy Analytical Hierarchy Process) method is based on the principle of pair-

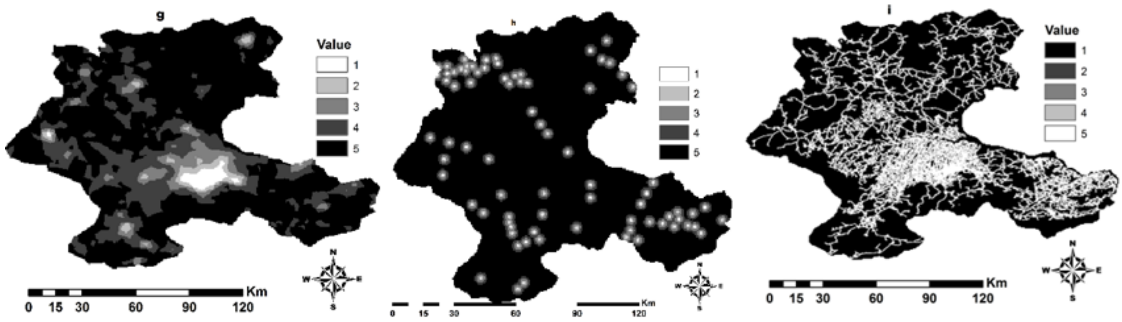

Fig. 5: Anthropogenic datasets (city lights (g), point density of mining sites (h), distance to road (i).

wise comparison of the relative importance of criteria by numerical gradations as in the AHP method (Alaneme et al. 2021). Since decision-making is a common problem, The FAHP technique was developed to solve this problem, and this technique aims to express the approximate choice of decision-makers by choosing fuzzy numbers for criteria. FAHP is one of the preferred methods by researchers to analyze decision problems in many different fields, including site selection studies (Kahraman 2008). Criteria ratings are assigned by expert decision-makers in the fields of astronomical observations, earth sciences, meteorology, and urban planning (Yılmaz 2023). The criteria ratings determined by the experts are shown in the FAHP matrix (see Table 4). When comparing the two criteria, the criteria scores assigned by the experts are shown in (Table 3). When the importance of the two criteria (l,m,u) is equal, the values (1,1,1) are chosen, and the FAHP technique was used to determine the criteria weights. If the experts' pairwise comparisons are consistent, the criterion weights can be used for assignment. The experts' benchmarking data should be used in the AHP matrix to check consistency. CR (consistency ratio) can be calculated using CI (consistency index) (Saaty 1980). If the CR is less than 0.1, the judgments are consistent and the calculated criterion weights can be used. The formulas for calculating CR are shown simply, see Eq. (2). $\lambda_{\max}$ is the largest eigenvalue of the comparison matrix (Yılmaz 2023). The consistency index of a randomly generated reciprocal matrix is called random inconsistency (RI), and the value of random inconsistency for a study consisting of 9 criteria is R.I=1.45.

$$\mathrm{CI} = \frac{\lambda_{\max} - 1}{n - 1}. \tag{1}$$

In addition, to check the consistency of the created matrix (Saaty 1980), the consistency ratio (CR) value should be determined. The CR formula is shown below,

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{2}$$

CI = 0.102, RI (n = 9) = 1.45, CR = 0.071. The matrix obtained by the experts by pairwise comparisons (see Table 4) is consistent and can be used in the analysis phase.

4. MCDA METHODS

4.1. Fuzzy AHP

The origin of fuzzy theory dates back to the mid-nineteenth century (Zadeh 1965). There are several fuzzy AHP methods (Bozbura et al. 2007). In this study, the criteria weights were calculated using Buckley's FAHP. This method is an easily applicable and reliable method that is preferred in many studies (Beskese et al. 2015). In this method, triangular numbers are used to calculate the uncertainties of the parameters in our study. The mathematical operations of fuzzy numbers are described in detail in Zimmermann (2011) and Beskese et al. (2015). The uncertainties of the criteria were calculated using triangular fuzzy numbers (TFN) (l,m,u) when the most suitable sites were proposed for the construction of the observatory. The decision-makers (criteria, detailed criteria, and alternatives) were determined by pairwise comparisons. For the pairwise comparisons, the decision matrix A was created using the linguistic scale and the corresponding triangular fuzzy numbers (see Table 3).

The decision matrix is formed as a result of pairwise comparisons of experts;

$$\tilde{C}^k = \begin{pmatrix} 1 & \tilde{c}^k_{12} & \cdot & \cdot & \cdot & \tilde{c}^k_{1n} \\ \tilde{c}^k_{21} & 1 & \cdot & \cdot & \cdot & \tilde{c}^k_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \tilde{c}^k_{m1} & \tilde{c}^k_{m2} & & & & 1 \end{pmatrix}. \tag{3}$$

In the matrix, c^k_{ij} represents the triangular fuzzy number when the expert k compares criteria i and j.

Table 3: Fuzzy AHP scale.

Definition	Triangular fuzzy number	Reciprocal fuzzy number	Degree of importance
Equal importance	(1, 1, 1)	(1, 1, 1)	1
Moderate importance	(1, 3, 5)	(1/5,1/3,1)	3
Strong importance	(3, 5, 7)	(1/7,1/5,1/3)	5
Very strong or demonstrated importance	(5, 7, 9)	(1/9,1/7,1/5)	7
Extreme importance	(7, 9, 9)	(1/9,1/9,1/7)	9

$$\tilde{c}_{ij}^{k} = \begin{pmatrix} i > j, & (1,\,1,\,3),\ (1,\,3,\,5),\ (3,\,5,\,7),\ (5,\,7,\,9),\ (7,\,9,\,9) \\ i = j, & (1,\,1,\,1) \\ i < j, & (1/3,\,1,\,1),\ (1/5,\,1/3,\,1),\ (1/7,\,1/5,\,1/3),\ (1/9,\,1/7,\,1/5),\ (1/9,\,1/9,\,1/7) \end{pmatrix}. \tag{4}$$

$i > j$ means that the criterion j is less important than the criterion i and this is represented in the matrix as c_{ij}, $i = j$ means that the criteria are equally important. If $j > i$ this means that the criterion j is more important than the criterion i which is defined in the matrix as $1/c_{ij}$ (Table 3 (i)). In order for the decision matrix to clearly reflect the opinion of each expert, the geometric mean of each pairwise comparison is taken.

$$\tilde{a}_{ij} = \sqrt[K]{\tilde{c}_{ij}^{1} \otimes \tilde{c}_{ij}^{2} \otimes \ldots \tilde{c}_{ij}^{K}}\ . \tag{5}$$

Here, K represents the number of decision experts and $\oplus$ represents the fuzzy multiplication.

$$\tilde{r}_i = \sqrt[n]{\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \ldots \otimes \tilde{a}_{in}} \tag{6}$$

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n)^{-1}. \tag{7}$$

The fuzzy weighted decision matrix was constructed using the Buckley method of Kahraman and Çebı (2009) and Beskese et al. (2015), where a_{ij} is the total fuzzy evaluation value of criterion i with criterion j, r_i is the geometric mean of the fuzzy evaluation value of the criterion i with respect to each criterion, w_i is the weight of the criterion i, and $\oplus$ is the fuzzy addition sign. After the fuzzy weights of all criteria are determined, they are expressed by more precise values. One of the most widely used methods for the clarification process is the centroid method, which is based on the use of the centroid (Opricovic and Tzeng 2004, Beskese et al. 2015). Clarification calculations are followed by normalization calculations. These calculations (the importance weight of the r'th criterion w_r, for the n criteria) were performed using Eq. (4) (Beskese et al. 2015).

$$w_r = \frac{\tilde{w}_r}{\sum_{i=1}^{n} \tilde{w}_i} = \frac{w_{rl} + w_{rm} + w_{ru}}{\sum_{i=1}^{n} \tilde{w}_i}\ . \tag{8}$$

The 9 maps with data layers used in the study were overlaid in the program GIS concerning the criterion weights obtained by the FAHP method, and the most suitable locations for the construction of the observatory were proposed (see Fig. 6, red areas).

4.2. BWM

The BWM method is one of the MCDA methods in which criterion weights are calculated by pairwise comparisons with decision-makers. The decision-makers perform pairwise comparisons by assigning points between 1 and 9 to the criteria according to their importance. The BWM method leaves it up to the decision-makers to select the best and worst criteria among the criteria (Guo and Zhao 2017); Rezaei (2016). The decision-makers do not have to compare all the criteria with each other, but only the best and the worst criteria with the others. After this selection by the decision makers, a comparative mathematical method is applied to compare the best criterion with the other criteria and all other criteria with the worst criterion (Çakir and Melih 2019). This mathematical method can be summarized as a nonlinear optimization model that minimizes the maximum absolute difference (Labella et al. 2021). The application of the BMW method can be explained by the following steps;

Step 1: The decision criteria should be determined, Guo and Zhao (2017). If there are n criteria, $c_1, c_2 \ldots c_n$ stands for the i_{th} criterion (Liu et al. 2019).

Table 4: The FAHP pairwise comparison matrix. C1 - distance to roads, C2 - landslide, C3 - distance to active faults, C4 - Wind Speed C5 - point density of mining sites, C6 - city lights, C7 - Precipitable Water Vapor, C8 - Cloud Cover and C9 - DEM.)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1,1,1	0.14,0.2,0.33	0.2,0.33,1	0.14,0.2,0.33	0.11,0.14,0.2	0.11,0.14,0.2	0.11,0.11,0.14	0.11,0.11,0.14	0.11,0.11,0.14
C2	3,5,7	1,1,1	0.2,0.33,1	0.2,0.33,1	0.2,0.33,1	0.11,0.14,0.2	0.11,0.11,0.14	0.11,0.11,0.14	0.11,0.14,0.2
C3	1,3,5	1,3,5	1,1,1	0.14,0.2,0.33	0.2,0.33,1	0.11,0.14,0.2	0.11,0.11,0.14	0.11,0.11,0.14	0.14,0.2,0.33
C4	3,5,7	1,3,5	3,5,7	1,1,1	1,1,1	0.11,0.14,0.2	0.11,0.14,0.2	0.11,0.11,0.14	0.2,0.33,1
C5	5,7,9	1,3,5	1,3,5	1,1,1	1,1,1	0.2,0.33,1	0.2,0.33,1	0.14,0.2,0.33	0.2,0.33,1
C6	5,7,9	5,7,9	5,7,9	5,7,9	1,3,5	1,1,1	1,1,1	0.2,0.33,1	0.2,0.33,1
C7	7,9,9	7,9,9	7,9,9	5,7,9	1,3,5	1,1,1	1,1,1	0.2,0.33,1	1,1,1
C8	7,9,9	7,9,9	7,9,9	7,9,9	3,5,7	1,3,5	1,3,5	1,1,1	1,1,1
C9	7,9,9	5,7,9	1,3,5	1,3,5	1,3,5	1,3,5	1,1,1	1,1,1	1,1,1

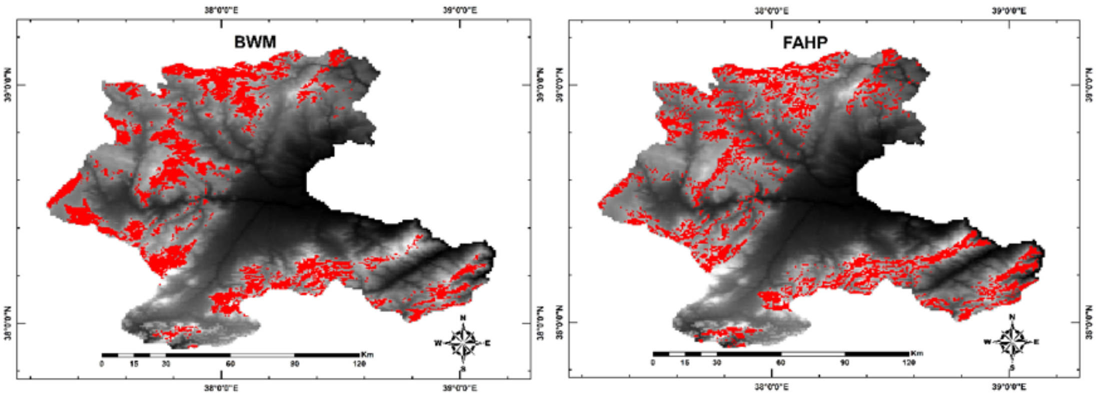

Fig. 6: Map of candidate sites for the astronomical observatory covered with DEM (marked in red).

Step 2: The best (most desirable, most important) and worst (least desirable, least important) criteria should be determined (Rezaei 2015).

Step 3: The importance of the best criterion determined by the decision maker compared to the other criteria is determined by choosing an integer between 1 and 9 (1: equally important, 3: moderately more important, 5: very important, 7: much more important, 9: extremely important). In this step, a vector called Best-Others (BO) is defined, moving from the best to the others. The same procedure is applied to the worst chosen criterion to define the vector worst-others (OW) that goes from worst to others (Çakir and Melih 2019, Ren et al. 2017, Fard et al. 2022).

$$\mathrm{BO} = (a_{B1}, a_{B2}, ...a_{Bn}) \tag{9}$$

$$\mathrm{OW} = (a_{1W}, a_{2W}, ...a_{nW})^T \tag{10}$$

a_{Bj} shows the preference of the best criterion B over the criterion j and a_{jW} shows the preference of the criterion j over the worst criterion W. As a result it should be a_{BB}=1, a_{WW}=1. These expressions represent the comparison of the best and worst criterion with itself, respectively (Rezaei 2016).

Step 4: Optimal weights (ω_1^*,ω_2^*,.....,ω_n^*) are reached by solving the linear problem (Eq. (11) (Rezaei 2016, Fard et al. 2022):

$$\min es.\ t. \begin{cases} |\omega_B - a_{Bj}\omega_j| \le e, \text{for all } j, \\ |\omega_j - a_{jW}\omega_W| \le e, \text{for all } j, \\ \sum_J \omega_J = 1, \\ \omega_J \ge 0, \text{for all } j. \end{cases} \tag{11}$$

5. RESULTS AND DISCUSSIONS

The article proposes new fuzzy AHP and BWM models for the simultaneous treatment of complex criteria in the decision-making process. The proposed fuzzy AHP and BWM model is used to solve the problem of site selection for an astronomical observatory. In the proposed model, after analysing many criteria composed of meteorological, geographical, and anthropogenic datasets, suitable sites are shown in red in the (Fig. 6). The most crucial criterion in the model is Cloud Cover. Meteorological datasets are more important than geographic and anthropogenic datasets in terms of weighting. The proposed areas are essential for decision-makers to constrain alternatives. This method should be supported by field tests and the final location should be determined.

Table 5: Criterion weights obtained by FAHP and BWM methods.

Decision criteria	BWM Weight	FAHP Weight	Rank
C1	0,02204	0,01344	9
C2	0,04023	0,02727	8
C3	0,04023	0,02732	7
C4	0,04526	0,04812	6
C5	0,07242	0,07335	5
C6	0,12070	0,15998	4
C7	0,12070	0,17878	3
C8	0,28023	0,27807	1
C9	0,25819	0,19403	2
Sum	1,000	1,000	
Average Ksi*	0,081	C.R	0,071

The estimated mean Ksi* of BWM is 0.081. Ksi*, the closeness of Ksi to zero increases the reliability of expert benchmarks (Rezaei 2017). The maximum acceptable limit of the consistency ratio for the nine-point scale and nine decision criteria is 0.4747 (see Table 6). Therefore, it can be concluded that the calculated results are reliable and acceptable (Chowdhury and Haque Munim 2022).

The consistency ratio (CR) of FAHP expert benchmarks $\in [0, 1]$. In our study, the value CR was calculated to be 0,071. Reliability increases as the value CR approaches zero. If CR $\leq 0, 1$, the decision matrix is consistent (Wu et al. 2008). The BWM model functions similarly to the FAHP but uses fewer pairwise comparisons to determine criterion weights in a simpler manner (Chowdhury and Haque Munim 2022). The weight coefficient of the FAHP model has a lower consistency ratio than the BWM and the value of the weight coefficient is less reliable.

There are similarities and differences between the BWM criteria weights and the FAHP weights for the criteria used in studies to select sites for astronomical observatories, Table 5. While the criterion Cloud Cover was the most important criterion in the BWM method with 28%, a value close to the BWM method with 27.8% was the most important criterion in the FAHP method. The criterion DEM was found to be the second most important criterion in the ranking of criteria with 19.4% values in FAHP method and 5.8% in the BWM method. The criterion distance to the road was found to be the least important criterion in both MCDA methods. The criteria weights and their order are shown in Table 5. In addition, meteorological criteria were the most important group of criteria, with values of 50.4% by the FAHP method and 44.6% by the BWM method. Geographical criteria were the second most important criteria group with values of 32.1% by the FAHP method and 41.1% by the BWM method. It was found that anthropogenic criteria ranked third in the order of criteria groups with values of 24.6% according to the FAHP method and 21.5% according to the BWM method. According to the MCDA method, the Cloud Cover, Precipitable Water Vapor, DEM, and city lights criteria have a large share in the weighting of all criteria with total values of 81% by the FAHP method and 77.9% by the BWM method. In the proposed model, the FAHP and BWM methods were used separately to determine the weighting of many criteria consisting of meteorological, geographic, and anthropogenic datasets. These two approaches were used to obtain two different result maps (see Fig. 6) comparing the results and criteria weights. The most important criterion of the model is Cloud Cover. Meteorological datasets are more important than geographic and anthropogenic datasets in terms of weighting. The proposed areas are important for decision-makers to constrain alternatives. This method was to be substantiated by field trials, and the final location was to be determined. The objective of the study was to present the factors affecting the site selection for an optical astronomical observatory and to present alternative sites for the observatory in Malatya. The meteorological data group was identified as the most important group of criteria. Cloud Cover was identified as the most important criterion. Cloud Cover, Precipitable Water, DEM, and the lights of the city were identified as important decision criteria. according to fuzzy AHP, the most suitable areas constitute 16,73% of the working area, while according to the BWM model, it constitutes 16,45%. The most suitable areas determined by the FAHP method and the most suitable areas determined by the BWM method overlap. In both methods, the amount of overlapping surfaces is very large. Since these areas result from two methods, we recommend that they be tested primarily in field trials. Since the increase of aerosols in the atmosphere has a negative effect on atmospheric visibility, it is not preferred for astronomical observations (Solmaz et al. 2021, Varela et al. 2008). Aerosol Optical Depth (AOD) is the most commonly used dataset for estimating aerosol content in the air (Koçak and Ebrahimi 2020, Aksaker et al. 2015).

It can be related to the work to be done by adding AOD to the meteorological datasets we use in similar studies. The astronomical observatory site selection is open to the use of different MCDM methods.

While our study suggests the best alternative areas to build the observatory to operate at maximum optical efficiency, it is important in terms of saving time and energy by limiting alternative areas within the study area and demonstrates the applicability of various MCDA methods in observatory siting studies. When deciding on the final site, it is important to support the areas proposed in our study with field measurements.

Table 6: Criterion for a 9-point pairwise comparison scale.

Criteria	3	4	5	6	7	8	9
Consistency rate (for 9-point pairwise comparison scale)	0,2122	0,3653	0,4055	0,4225	0,4445	0,4587	0,4747

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APPENDIX

LIST OF ABBREVIATIONS

(GIS) Geographic Information System
(FAHP) Fuzzy Analytical Hierarchy Process
(AHP) Analytical Hierarchy Process
(MCDA) Multi-Criteria Decision Analysis
(BWM) Best Worst Method
(MODIS) Moderate Resolution Imaging Spectroradiometer
(VIS) Spectral Bands With Wavelengths In The Visible
(NSIDC) National Snow and Ice Data Center
(LAADS) Atmosphere Archive and Distribution System
(HDF) Hierarchical Data Format
(AVHRR) Advanced Very High Resolution Radiometer
(DTU) Technical College of Denmark
(GWA) Global Wind Atlas
(DEM) Digital Elevation Model
(SRTM) Shuttle Radar Topography Mission
(USGS) U.S. Geological Survey.
(MTA) General Directorate of Mineral Research and Exploration
(EOG) The Earth Observation Group
(VIIRS)The Visible and Infrared Imaging Package
(JPSS) Joint Polar Satellite System
(JSON) JavaScript Object Notation
(KML) Keyhole Markup Language
(GTOPO30) Global 30 Arc-Second Elevation
(C.R) Consistency Ratio
(C.I) Consistency İndex
(TFN) Triangular Fuzzy Numbers
(BO) Best-Others
(OW) Worst- Others
(AOD) Aerosol Optical Depth

ИЗБОР ЛОКАЦИЈЕ ЗА АСТРОНОМСКУ ОПСЕРВАТОРИЈУ КОРИШЋЕЊЕМ FUZZY AHP И BWM МЕТОДА

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Стручни чланак

Успостављање опсерваторије често укључује сложене одлуке, попут избора локације, на основу више критеријума који међусобно могу бити супротстављени. У овој студији развијамо процес анализе одлучивања заснованог на вишеструким критеријумима који комбинује анализу Географског Информационог Система (GIS) са Вишекритеријумском анализом одлука (MCDA), и користи овај процес за одређивање најприкладнијих локација за изградњу опсерваторије у урбаном подручју Малатије. GIS је коришћен за прорачун, класификацију и анализу критеријума, док су FAHP (Расплинути аналитички хијерархијски процеси, Баклијева метода) и BWM (тип MCDA метода, тзв. најбољи-најгори метод) методе коришћене за отежавање критеријума одлучивања и процену њихових утицаја на избор алтернативне локације. Док је критеријум "прекривености облацима" у BWM методи био најважнији критеријум са 28%, вредност најважнијег критеријума у FAHP методи је упоредива и износи 27,8%. Метеоролошки критеријуми били су најважнија група критеријума са вредностима од 50,4% према FAHP методи, и 44,6% према BWM методи. Студија се заснива на метеоролошким, географским и антропогеним скуповима података, предлажући најприкладније локације за астрономске опсерваторије унутар граница овде проучаваног подручја. Предложене локације су резултат избора локације, који је прва фаза избора локације за астрономске опсерваторије. Избор локације је важан за ограничавање броја алтернативних локација. Неопходно је спровести теренске тестове међу предложеним подручјима и одабрати коначну локацију према резултатима. Успешна употреба GIS-а и више од једне MCDA методе отвориће пут за развој различитих метода за одређивање локације астрономске опсерваторије.