

Sustainable land management under uncertainty: A hybrid Bayesian BWM and RPM framework for spatial prioritization

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Abstract: Sustainable land management is a complex problem due to environmental constraints and decision-maker uncertainty. This study presents an integrated solution combining Geographic Information Systems (GIS), the Bayesian Best-Worst Method (Bayesian BWM), and the Ratio Product Model (RPM) to improve the accuracy of spatial prioritization in land-use decisions. The integration of the Bayesian BWM and RPM statistically minimizes the cognitive uncertainty in expert opinions whilst enabling the most suitable areas to be ranked with precision within their own categories, without any normalization constraints. The proposed model was developed for three main categories—residential, industrial, and agricultural—in the province of Balıkesir. The analysis results revealed that the ‘ease of access to services’ (0.5660) criterion was the most decisive factor for residential suitability, whilst ‘distance to power transmission lines’ (0.1322) and ‘average rainfall’ (0.1315) were the most decisive factors for industry and agriculture, respectively. The suitability maps show that the Bandırma-Susurluk corridor is strategically prioritized for industry, whilst the Manyas-Gönen basin is prioritized for agricultural production. RPM scores (0.2750 for settlement, 0.6036 for industry, and 0.3868 for agriculture) quantify implementation priorities, providing a reliable decision-support tool for managing uncertainty in spatial planning.

Keywords: Sustainable land management; spatial prioritization; Bayesian BWM; ratio product model (RPM); GIS-based MCDM

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1. Introduction

The earth, the land on which we are born, grow up, and grow old, contains the effects of all our lives. From the past to the present, the effects of human activities on the land have been increasing exponentially. The most important of these effects are rapidly increasing urbanization activities. More than half of the human population has lived in cities since 2008. The urban population rate in the world has increased to 56 percent by 2021. This rate is estimated to reach 68% by 2050 (UN-Habitat, 2022).

Increasing population and economic growth in the world increase the continuous impacts of human activities on land use. These impacts bring a range of complexities to environmental and land resource development (Chen, 2014). Accurate land assessment is important in land use planning and provides critical information to support sustainable land use. The assessment of land for sustainable land use (SLM) considers many aspects, including natural conditions, economic, social, and environmental development conditions (Dinh & Tran, 2012). As discussed by Krüger et al. (2013), effective land-use monitoring requires consistent and high-quality topographic data. In line with this, our study utilizes high-resolution datasets to ensure the precision of the suitability analysis. FAO (Food and Agriculture Organization of the United Nations) defines SLU as the suitability of land for its intended use, i.e., the appropriate use of land based on sustainable methods (FAO, 1976). Indeed, to make correct and effective resource management and planned decisions, optimum land uses aiming at ecological protection should be determined and maintained precisely. In

this sense, the basic principle of sustainability is to conduct and implement land use suitability analyses (Cengiz et al., 2013; Van Lier, 1998; Bagheri et al., 2012; Kang et al., 2021). The main objective of land suitability analysis is to estimate the natural capacity of a land unit and support specific land uses without long-term degradation. Land suitability analysis that considers environmental and socioeconomic criteria is the most important tool for achieving sustainable development (Ferretti & Pomarico, 2013; Malmir et al., 2016; Aliani et al., 2021). Land suitability analysis is an interdisciplinary approach (Herrmann & Osinski, 1999; Groot, 2006; Sarapirome & Charunghthanakij, 2012) and is a complex process that helps to identify suitable sites by taking into account different criteria, limitations, or specific characteristics, as well as taking into account various environmental and socioeconomic criteria and filtering out unsuitable or less suitable sites (Cengiz et al., 2013; Chen, 2014; Xu et al., 2021; Aliani et al., 2021).

Since the 1990s, SLU based on geographic information systems (GIS) has increasingly become integral to urban, regional, and environmental planning activities (Xie et al., 2026; Orhan et al., 2025; Lotfi et al., 2009; Aliani et al., 2021). This interest in the use of GIS in the field of SLU is continuing. GIS is an effective tool for linking spatial data that answers location-based queries and provides decision-makers and planners with helpful information for planning and making appropriate decisions (De Toro & Iodice, 2016; Aliani et al., 2021). Since land suitability is a complex process requiring multiple criteria, it requires decision-making techniques that aim to select a solution or prioritize solutions among the available solutions (Chen, 2014; Aliani et al., 2021). Optimizing land-use allocation has been a longstanding challenge in geospatial science, often requiring a balance between heuristic and exact methods (Cromley & Hanink, 2003). Building on these foundational discussions, our framework introduces RPM to prioritize spatial suitability without the constraints of traditional normalization. SLU analyses have often been addressed using multi-criteria decision analysis (MCDA) (Antoine et al., 1997; Herrman and Osinski, 1999; Dinh & Tran, 2012; Xu et al., 2021; Kang et al., 2021). The integration of MCDA and GIS to create visualized different suitability maps for users and decision-makers has been effectively used to determine the suitability of SLU, to solve spatial problems in urban assessment and planning, and to select spatially appropriate locations (Phua & Minowa, 2005; Chen, 2014).

SLU is one of the fields where multi-criteria decision-making and GIS can successfully interact (Aliani et al., 2021). Over the past thirty years, GIS-based decision-making techniques (MCDMs) have become appealing to various scientific disciplines, and researchers have introduced, developed, and applied methods to integrate these techniques with SLU. Since land suitability analyses inherently involve the integration of complex spatial data and multiple criteria, the management of uncertainty is of critical importance in these processes. Specifically, the quality and consistency of spatial data play a decisive role in the precision of analysis results, as emphasized by Krüger et al. (2013). Furthermore, Romero and Clarke (2017) highlighted the presence of intrinsic uncertainties in the extraction of terrain features and demonstrated the importance of multi-method approaches to manage these uncertainties. However, uncertainty in spatial planning is not limited to data-driven technical errors. The subjective judgments exhibited by decision-makers when evaluating criteria introduce cognitive and epistemic uncertainties into the process. Traditional deterministic methods tend to neglect this layer of uncertainty by treating parameters as crisp values. Yet, sustainable land management requires robust decision support mechanisms that explicitly define and model these uncertainties stemming from both data and expert opinions. In this context, numerous studies related to SLU have been conducted using the Bayesian Worst-Best Method (BWM), a multi-criteria decision-making technique (Konurhan et al., 2023; Wang et al., 2024; Konurhan et al., 2023b; Koç et al., 2024). To the author's knowledge, no studies have been found that integrate GIS and MCDM methods with the Ratio Product Model (RPM) method. This study aims to integrate the RPM method, a new method, with the Bayesian BWM (Best Worst Method).

This study aims to determine the suitable land use types (such as residential, industrial, and agricultural) that are appropriate for sustainable land use. The Bayesian BWM and RPM were used in an integrated manner to identify suitable areas. Bayesian Networks (BNs) are mathematical models that facilitate comparisons under uncertainty and offer significant advantages in modeling both qualitative and quantitative variables (Salvador et al., 2022; Konurhan et al., 2023). BN has also been used in solving decision-making problems (Bhandari et al., 2015; Yazdi, 2019; Konurhan et al., 2023). The Bayesian BWM method is an enhanced version of the classical BWM method, based on pairwise comparisons. It is designed to manage uncertainties and inconsistencies more effectively by leveraging expert opinions and insights. In this study, criterion weightings were performed using this Bayesian BWM method. Following the weighting process, the RPM method was used to rank the alternatives. The RPM method offers a normalization-independent and ranking-preserving approach in multi-criteria decision-making problems, enabling the determination of the relative priorities of alternatives (Mohammadi & Rezaei, 2023). These methods were analyzed in the GIS environment, with suitability scores calculated for the most appropriate class identified in each category. Maps of areas suitable for sustainable land use are being created in line with the weight values determined using GIS tools. GIS tools were utilized to produce spatial data within the scope of the study. The study area is the province of Balıkesir, situated in northwestern Türkiye. The province, situated in the Marmara Region of the country, is bordered by the Marmara and Aegean Seas. It has an approximate area of 14,604 km².

Within sustainable land use planning, integrating GIS and MCDM methods has become the main analysis framework for agriculture, settlement, and urban development studies in recent years. Integrating methods such as AHP, TOPSIS, and BWM with GIS makes it possible to analyze different criteria and provide visual support to decision-makers spatially (Chen, 2014; Aburas et al., 2015). For instance, recent research published in Cartography and GIS has demonstrated the evolving capacity of Spatial Multi-Criteria Evaluation (MCE) in complex environments, such as 3D urban suitability analysis (Munn & Dragičević, 2020). While such studies focus on dimensional expansion and complex urban structures, this study complements the existing scholarship by addressing decision-maker uncertainty through probabilistic methods like Bayesian BWM and RPM. Luan et al. (2021) demonstrated the effectiveness of soft computations in decision support processes by comparing OWA and LSP methods in multi-scenario land use planning. Yalew et al. (2016) analyzed suitable areas for agriculture in the Abbay Basin in Ethiopia using AHP and GIS-based weighted overlay method and emphasized that biophysical factors are decisive. Bozdağ et al. (2016) successfully applied the AHP-GIS approach integrating topography, climate, groundwater, and soil data to increase agricultural productivity in Cihanbeyli district in Türkiye. Konurhan (2023) used BWM and GIS integration in sustainable urban development to identify areas suitable for settlement in Çanakkale province. Akıncı et al. (2013) integrated AHP-GIS integration into agricultural suitability analysis in Türkiye and drew attention to the importance of spatial decision support systems in planning. Similarly, in the study conducted in Artvin, the effect of natural factors such as slope and land class on suitability was emphasized. As one of the advanced examples, Foroozesh et al. (2022) presented a decision support model for sustainable urban development in Karaj City by integrating BWM, AHP, and TOPSIS methods with GIS. Chen (2014) produced land suitability maps for urban expansion by considering socio-economic factors such as population, income, and employment in Regina, Canada. Luan et al. (2021) demonstrated the importance of multi-scenario planning by analyzing different scenarios, such as agriculture and industry.

This study is a multi-criteria land suitability assessment conducted for the province of Balıkesir. It is known that there are limited studies of similar scale and scope in the literature for this region. Therefore, the aim is to conduct a comprehensive land use assessment for the province of Balıkesir. It offers methodological diversity in evaluating different land use

scenarios (e.g., agriculture, settlement, industry) within the same analytical framework, utilizing GIS-based Bayesian BWM and RPM methods in tandem. Furthermore, no study has been found that integrates the RPM method with GIS and MCDM methods, to the author's knowledge. In this respect, the study will contribute to literature by integrating regional planning and multi-criteria decision-making approaches. Moreover, while recent scholarship in Cartography and GIS has highlighted the necessity of multi-method approaches to handle uncertainties in terrain feature extraction (Romero and Clarke, 2017), this study extends this rigorous approach to uncertainty by applying Bayesian methods to the decision-making phase.

Consequently, the primary objective of this study is to identify the most suitable locations for residential, industrial, and agricultural areas within the framework of sustainable land management in the province of Balıkesir. The originality of this research lies in integrating, within a GIS environment, the RPM method—which does not require normalization and strictly prevents the compensation of weak criteria—with the Bayesian BWM, which probabilistically models decision-makers' cognitive uncertainties. This hybrid model addresses the spatial risk concealment problem frequently encountered in traditional methods, thereby providing a decision-support framework that is sensitive to uncertainty and reliable for regional planning.

2. Materials and Methods

The method employed in the study was designed to generate multi-land suitability for settlement, industry, and agriculture, and to prioritize the most suitable areas through the Bayesian BWM-RPM framework integrated with GIS. A diagram summarizing the workflow followed and showing the steps from data to final product is presented in Figure 1. The sequence of steps is shown as follows: obtaining criterion weights using Bayesian BWM, creating suitability maps in GIS, and ranking the most suitable class using RPM.

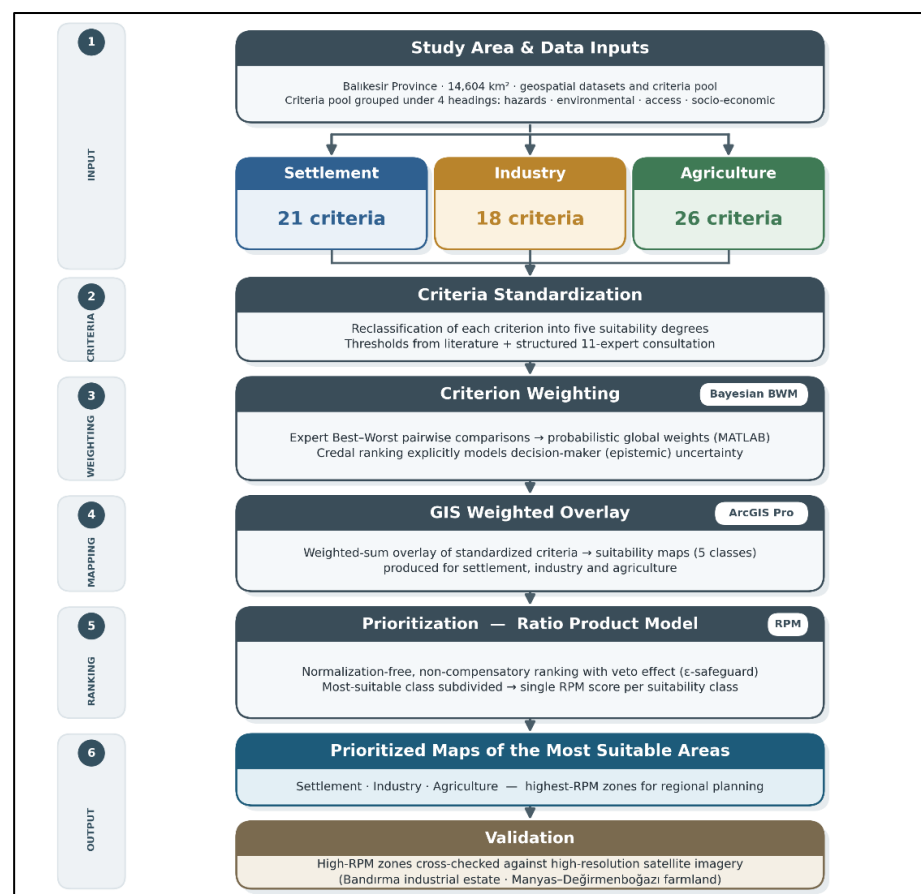


Figure 1. Flowchart of the study methodology

2.1. Study area

Balıkesir province is located between 39° 20' - 40° 30' north parallels and 26° 30' - 28° 30' east meridians northwest of Anatolian Peninsula in Türkiye. Its surface area is 14.604 km². The Marmara Sea surrounds it to the north, Bursa and Kütahya to the east, Manisa and İzmir to the south, the Aegean Sea to the west, and Çanakkale to the northwest (Figure 2).

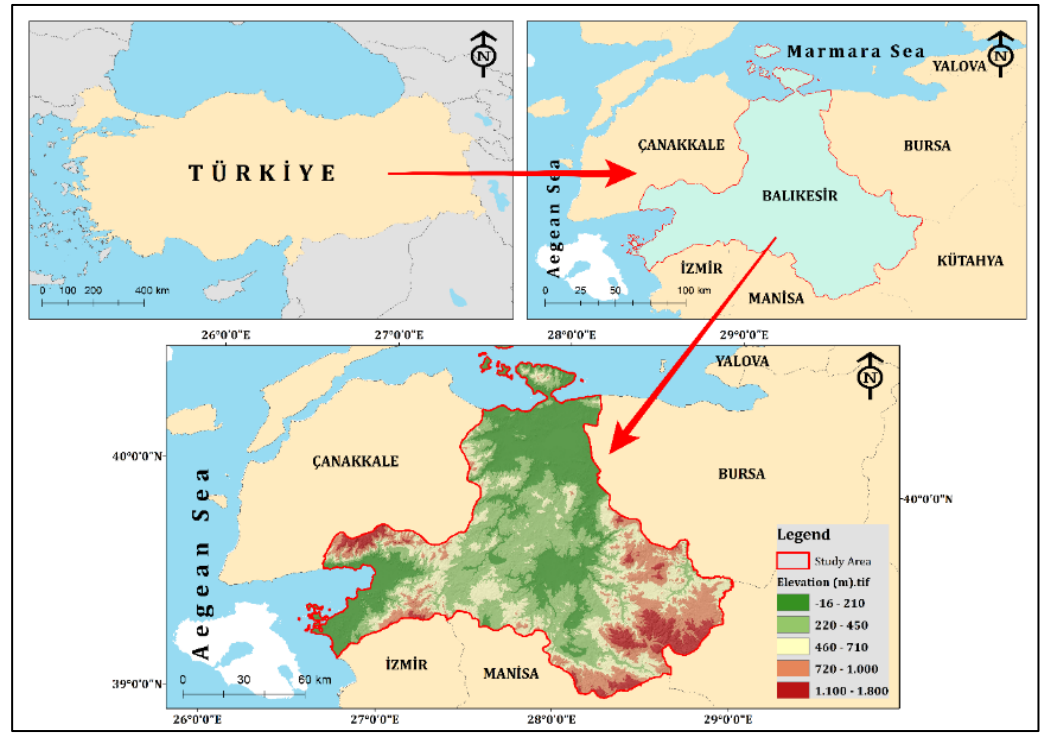


Figure 2. Study area

Balıkesir Province is one of the provinces with two coasts as it has both Marmara Sea and Aegean Sea coasts. It has a total coast of 290.5 km, 175 km to the Marmara Sea, and 115 km to the Aegean Sea (Aydın, 2013). The landforms of the study area, which is not very hilly, consist mainly of undulating plains. River valleys fragment the plateau plains, covering over half of the province area. The northern part of the province, which does not reach 2000 m in height, is generally ruggedized by the western extensions of Karadağ. The southeastern and south-western parts of the province are more mountainous. The peak of Ulus Mountain, which is connected to the Alaçam Mountains in the southeast, reaches 1769 meters. Kaz Mountains in the southwest-northeast direction reaches a height of 1774 m at Karataş Hill on the provincial border (<https://balikesir.ktb.gov.tr/tr-65836/fiziki-ozellikler.html>).

The climate characteristics of Balıkesir province are in a transition zone between the Mediterranean and Black Sea climates. On the Aegean coasts, summers are hot and dry, winters are mild, and the Mediterranean climate is generally rainy. In contrast, summers are relatively calm on the Marmara coasts under the influence of the Black Sea climate. As one moves inland from the coasts, it is noticeable that the continental climate is dominant, especially in the provincial center (Özey, 2016). According to the meteorological observation data for the period 1927-2024, the average annual temperature in the study area is 12.0 °C, the average annual total sunshine duration is 6.7 hours, the average annual number of rainy days is 103.2, and the average annual precipitation is 392.3 mm. The annual average highest temperature is 17.9 °C, and the annual average lowest temperature is 6.4 °C. The prevailing wind direction is north, and the secondary wind direction is north-northeast, depending on seasonal changes (<https://www.mgm.gov.tr/veridegerlendirme/il-ve-ilceler-istatistik.aspx?k=A>). Development of agriculture, animal husbandry, and tourism sectors, growth of industrial sectors, and population increase in Balıkesir province have triggered

increased environmental pollution. Balıkesir has many popular destinations, such as Mount Ida and Lake Manyas, for tourism activities, flora and fauna, and environmental protection zones (Tercan, 2021).

In the province of Balıkesir, there is intense spatial competition between land uses for agricultural, industrial, and settlement purposes. Consequently, the province serves as an ideal and highly complex geographical laboratory for testing a multiplicative model such as the RPM, which, by its very nature, does not allow for compensation and strictly penalizes flawed land-use distributions.

2.2. Parameters used in the land suitability assessment

This study deals with determining areas suitable for settlements and agricultural and industrial areas, which are the most basic land-use classes. In this direction, criteria were determined for the land classes determined by considering the study area's characteristics and the literature sources. Considering the survey method for all land classes, criteria were determined under four main headings: natural disasters, environmental factors, infrastructure and access, and socio-economic conditions. Accordingly, a total of 22 criteria were determined for areas suitable for settlement, 16 criteria for determining areas suitable for industry, and 18 criteria for determining suitable agricultural areas. Care was taken to determine the criteria for land classes according to the characteristics of the study area and literature sources. Each criterion was included in the criteria pool after necessary evaluations. Below are the characteristics of the criteria for the land classes to be determined, why they were selected, and their status in the study area.

Specific threshold values for each criterion (e.g., 0–2° for high slope suitability) have been established to ensure scientific validity. Although most threshold values have been taken directly from the existing literature, as indicated by specific references in the suitability tables, some criteria have required locally specific adjustments. Threshold values clearly marked as 'expert' in the reference column have been determined through a structured expert consultation process. To this end, opinions were sought from 11 experts. These experts comprise academics from the fields of Geography (4), Urban and Regional Planning (3), Emergency and Disaster Management (2), and Industrial Engineering (2). Each expert possesses at least five years of academic or professional experience in spatial analysis and regional planning.

2.2.1. Selection of criteria for settlement areas

A total of 21 criteria were selected under four main headings for suitable areas for settlement (Table 1). The criteria for determining suitable areas were classified according to their characteristics, and the suitability degrees were determined according to literature sources and study area characteristics (Table 2).

Table 1. Criteria used for areas suitable for settlement

Natural Factors	Environmental Factors	Infrastructure and Access	Socio-Economic Factors
Elevation (a1)	Distance to Lakes (b1)	Distance to Residential Areas (c1)	Population Density (d1)
Slope (a2)	Distance to Stream (b2)	Distance to Main Road (c2)	Distance to Historical and Cultural Areas (d2)
Aspect (a3)	Distance to Environmental Protection Areas (b3)	Distance to Railway (c3)	Ease of Access to Services (School, Hospital, Park-Garden, Bank, Theatre, Restaurant etc.) (d3)
Soil Type (a4)	Average Precipitation (b4)	Distance to Power Lines (c4)	Distance to Industrial Facilities (d4)
Earthquake Risk (Distance to Fault Lines) (a5)	Average Temperature (b5)	Distance to Health Centers (State Hospitals and Large Private Hospitals) (c5)	
Geological (a6)	Vegetation (NDVI) (b6)		

Elevation and slope criteria are frequently used in settlement suitability analyses. Seafront areas are not suitable for settlements due to high groundwater levels. Very high and sloping areas are unsuitable for settlement due to several problems related to slope constraints, landslides, increased construction costs, and protected land use (Aliani et al., 2021). It is stated that the elevation between 0-200 m is especially highly suitable for settlements. Between 200-500 m is categorized as suitable areas. Generally, elevations above 500-700 m are considered less suitable for settlements. Regarding slope values, 0-2° slope values are categorized as the most suitable areas, while slope values above 15° are unsuitable (Arnous, 2013; Liu et al., 2014; Konurhan, 2023). The study area's elevation varies between 0-1767 m and slope values between 0-71°. Elevation and slope values increase around the Alaçam, Ulus, and Civan Mountains around Dursunbey district in the southeast and Mandra and Kaz Mountains in the west. The altitude and slope values decrease in the central regions, which are among the most suitable settlement areas. Aspect is related to the direction of a point. In the northern hemisphere (NH), south-facing slopes offer a more favorable sun angle for settlements (Aliani et al., 2021). Therefore, south-facing slopes are the most suitable areas for settlement in the NH. Soil quality is related to water and rain penetration, and its resistance to stagnation in construction installations is significant. If the soil quality is not suitable for the passage of wastewater and sewage, cities will face some problems in the disposal of such water. Deep and heavy textured soils are the most suitable for settlements, while sandy soils are not the most suitable for developing settlements. The best place for urban development is profound, heavy-textured soil (Aliani et al., 2021). A suitable classification has been made for the study area. Earthquake risk is a very important criterion for settlements. The most suitable settlements are the areas away from fault lines and where the earthquake risk is low (Xu et al., 2011). Small-scale faults pass north, central, and south of the study area. According to these faults, appropriate classification has been created. It is very important that the ground is solid for areas suitable for settlement. Regarding the geological structure of the ground, intrusive igneous rocks and metamorphic rocks are more suitable for construction as they are rugged, durable, and have a low risk of collapse (Esen, 2019). There are geological units with solid ground in most of the central and southern parts of the study area, and these regions are classified as regions suitable for settlement. The distance of the settlement areas to water resources, transportation network, existing settlement areas, industrial centers, health centers, and historical cultural structures, that is, the location of the settlements, is critical. Such factors must be considered to establish settlements in a suitable location (Maktav et al., 2011; Zhang et al., 2013; Malmir et al., 2016; Luan et al., 2021). The criteria determined in this context were divided into appropriate classes and used in the analysis phase. Average temperature and precipitation are other important criterion for settlements. Precipitation of 500-800 mm and a temperature of 18-24 °C suit settlement areas (Makhdom, 2003). Considering these values, an appropriate classification was made and used in the study area. The density of vegetation cover for settlement areas is also important for environmental protection. Special environmental protection zones and national park areas, which may be dense in terms of forest cover, are not suitable for settlement. Areas with sparser vegetation cover are considered suitable for settlement (Zhang et al., 2013; Li et al., 2018). Distance to environmental protection areas and normalized difference vegetation index (NDVI) criteria were established for the study area. Accordingly, Balıkesir's Kaz Mountains, Lake Manyas, and Bird Sanctuary National Park areas are deemed unsuitable for settlement due to their dense forest cover and protected areas (Figure 3; Table 2).

Table 2. Criteria and standards for the sub-criteria used in the analysis of land suitability for urban development

Main Criteria	Sub-Criteria	Unsuitable	Low suitability	Medium suitability	High suitability	Very high suitability	Reference
Natural Factors	Elevation (a1)	>700m	600-700m	500-600m	200-500m	<200m	Liu et al., 2014; Aliani et al., 2021
	Slope (a2)	>15	8-15°	5-8°	2-5°	<2°	Arnous, 2013
	Aspect (a3)	Northern High Mountain Grassland Soils, Water Surfaces	Western	-	Eastern	Southern Vertisol, Non-calcareous Brown Soils	Expert
	Soil Type (a4)	Colluvial-Hydromorphic Soils	Alluvial Soils, Forest Soils	Reddish Brown Soils, Rendzinas			Aliani et al., 2021
	Earthquake Risk (Distance to Fault Lines) (a5)	<500	500-1000m	1000-1500m	1500-2000m	>2000m	Xu et al., 2011
	Geological (a6)	Alluvium and Current Sediments, Special Formations and Sedimentary Products	Pyroclastic Rocks and Volcanic Deposits	Extrusive Volcanic Rocks	Metamorphic Rocks, Sedimentary Rocks	Intrusive Rocks	Esen, 2019; Expert
Environmental Factors	Distance to Lakes (b1)	>200m	200-500m	500-800m	800-1000m	<1000m	Zhang et al. 2013
	Distance to Stream (b2)	>200m	200-500m	500-1000m	1000-2000m	<20000m	Zhang et al. 2013
	Distance to Environmental Protection Areas (b3)	>1000m	1000-1500	1500-2000m	2000-2500m	<2500	Malmir et al., 2016; Expert
	Average Precipitation (b4)	≥400mm-≤1000mm	400-450mm	450-500mm	500-600mm	600-800mm	Makhdom, 2003; Kang et al., 2021
	Average Temperature (b5)	8-10, ≥20 °C	10-12, ≥20 °C	18-20 °C	12-14 ,16-18 °C	14-16 °C	Kang et al., 2021
	Vegetation (NDVI) (b6)	Plant density= 0,32 - 0,64	Plant density= 0,25 - 0,31	Plant density= 0,18 - 0,24	Plant density= 0,0074-0,17	Plant density= >0.073	Expert
Infrastructure and Access	Distance to Residential Areas (c1)	>2000m	1500-2000m	1000-1500m	500-1000m	>500m	Maktav et al., 2011
	Distance to Main Road (c2)	<20,000m	10,000–20,000	5000-10.000m	2500-5000m	>2500m	Park et al., 2011
	Distance to Railway (c3)	<20,000m	10,000–20,000	5000-10.000m	2500-5000m	>2500m	Expert
	Distance to Power Lines (c4)	>90m	-	> 1000m	-	90-1000m	Malmir et al., 2016
	Distance to Health Centers (State Hospitals and Large Private Hospitals) (c5)	<20,000m	10,000–20,000	5000-10.000m	2500-5000m	>2500m	Expert
Socio-Economic Factors	Population Density (person) (d1)	>76.000- <12.000	12.000-18.000	19.000-28.000	49.000-75.000	29.000-48.000	Zhang et al., 2013; Expert
	Distance to Historical and Cultural Areas (d2)	>2500m	2500-5000m	5000-10.000m	<20,000m	10,000–20,000	Expert
	Ease of Access to Services (School, Hospital, Park-Garden, Bank, Theatre, Restaurant etc.) (d3)	<20,000m	10,000–20,000	5000-10.000m	2500-5000m	>2500m	Expert
	Distance to Industrial Facilities (d4)	<3000m	2000-3000m	1500–2000	400–1500m	>400m	Ustaoglu and Aydinoglu 2020

2.2.2. Selection of criteria for industrial areas

A total of 18 criteria under four main headings were evaluated for suitability for industrial areas (Table 3). The criteria used to determine suitable areas were classified according to their characteristics, and the suitability degrees were determined according to literature sources and study area characteristics (Table 4).

Table 3. Criteria and standards for the sub-criteria used in the analysis of land suitability for urban development

Natural Factors	Environmental Factors	Infrastructure and Access	Socio-Economic Factors
Elevation (a1)	Distance to Water Bodies (b1)	Distance to Main Road Network (c1)	Proximity to Markets (Distance to City Centers and Big Cities) (d1)
Slope (a2)	Groundwater Level (b2)	Distance to Railway (c2)	Proximity to Residential Areas (d2)
Aspect (a3)	Vegetation Density (b3)	Proximity to Ports (c3)	Proximity to Existing Industrial Zones (d3)
Earthquake Risk (Distance to Fault Lines) (a4)	Distance to Agricultural Areas (b4)	Distance to Airport (c4)	Distance to Health Centers (d4)
	Distance to Environmental Protection Areas / National Parks (b5)	Distance to Energy Transmission Lines (c5)	

The suitability of industrial zones to be established in a region is very important for the sustainable continuation of industrial facilities. The elevation between 801-1200 m may be suitable for the location of industrial facilities (Ramya & Devadas, 2019) and areas less than 15 m (Muhsin et al., 2018). Therefore, suitable elevation steps for the location of industrial facilities vary according to the characteristics of the study area. In this framework, the elevation step between 0-500 m is classified as suitable for the location of industrial facilities. Another criterion for the location of industrial facilities is the slope criterion. From both construction and environmental perspectives, the appropriate slope value for industrial facility construction is 0-10% to facilitate infrastructure provision and reduce environmental degradation (Reisi et al., 2018). Hence, 0-10% slope values were considered appropriate for the study area. Another factor in industrial plant site selection is environmental factors. Within the main criterion of environmental factors, criteria such as distance to lake areas, groundwater level, plant density, agricultural areas, and distance to protected areas -national parks- were evaluated. Industrial waste near the industrial facility can pollute surface water and groundwater. It is also emphasized that an industrial facility to be established should be at least 1,600 m away from surface waters to prevent industrial pollution (Reisi et al., 2018), as it is said that a distance between 0-500 m from surface waters would be appropriate (Ramya & Devadas, 2019; Muhsin et al., 2018). It is said that industrial facilities should be at least 53 m away from groundwater sources (Reisi et al., 2011). Accordingly, areas at least 1000 m away from the water sources of industrial facilities in the study area are considered suitable. Plant density and the distance to special environmental protection areas such as national parks are important for the location of industrial facilities. To ensure a balanced ecosystem, forest reserves should not be disturbed, and the least dense areas should be selected considering the plant density of the industrial facilities to be established (Ramya and Devadas, 2019). A buffer zone of 1000 m should be established for protected areas and their surroundings (Reisi et al., 2018). There are protected areas such as Kuşçenneti (Manyas) National Park, Kazdağı National Park, and Sarımsaklı Nature Park in the study area. Suitability classification was carried out by considering these protected areas. The distance from industrial facilities to agricultural areas should be at least 50 m (Muhsin et al., 2018). Accordingly, appropriate classification was made for agricultural areas in the study area.

Table 4. Criteria and standards for the sub-criteria used in the analysis of land suitability for industrial areas

Main Criteria	Sub-Criteria	Unsuitable	Low suitability	Medium suitability	High suitability	Very high suitability	Reference
Natural Factors	Elevation	>700m	600-700m	500-600m	200-500m	<200m	Liu et al., 2014; Aliani et al., 2021
	Slope	>10°	8°-10°	5-8°	2-5°	<2°	Reisi et al., 2018
	Aspect	Northern	Western	-	Eastern	Southern	Expert
	Earthquake Risk (Distance to Fault Lines)	<500	500-1000m	1000-1500m	1500-2000m	>2000m	Xu et al., 2011
Environmental Factors	Distance to Water Bodies (Lake, river and Dam)	<1000m	800-1000m	900-1000m	950-1000m	>1000m	Expert
	Groundwater Level	<53m	50-51m	51-52m	52-53m	>53m	Reisi et al., 2011
	Vegetation Density	Plant density= 0,32 - 0,64	Plant density= 0,25 - 0,31	Plant density= 0,18 - 0,24	Plant density= 0,0074- 0,17	Plant density= >0.073	Expert
	Distance to Agricultural Areas	<50m	50-100m	100-150m	150-200m	>200m	Muhsin et al., 2018; Expert
	Distance to Environmental Protection Areas / National Parks	>1000m	1000-1500m	1500-2000m	2000-2500m	<2500m	Muhsin et al., 2018
Infrastructure and Access	Distance to Main Road Network	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Sarapirome and Charungthanakij, 2012
	Distance to Railway	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Rikalovic et al., 2014
	Proximity to Ports	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Muhsin et al., 2018
	Distance to Airport	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Nuhu et al., 2022
	Distance to Energy Transmission Lines	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Sarapirome and Charungthanakij, 2012
Socio-Economic Factors	Proximity to Markets (Distance to City Centers and Big Cities)	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Sarapirome and Charungthanakij, 2012; Nuhu et al., 2022
	Proximity to Residential Areas	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Sarapirome and Charungthanakij, 2012; Nuhu et al., 2022
	Proximity to Existing Industrial Zones	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Sarapirome and Charungthanakij, 2012; Nuhu et al., 2022
	Distance to Hospital	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Expert

The geographical location of an industrial facility to be established is also very important. The distance of an industrial facility to the main road, railway, ports, airports, and energy lines is critical for the development and growth of that facility. Access to industrial facilities is important due to factors such as raw material exchange, produced goods delivery, and labor force access. Generally, a distance between 0-1000 m is considered appropriate (Sarapirome & Charungthanakij, 2012; Rikalovic et al., 2014; Muhsin et al., 2018; Nuhu et al., 2022). Finally, socio-economic factors such as distance to city centers, distance to existing industrial areas, and distance to all residential areas are also important for industrial facilities. Residential areas host important facilities such as banks, telecommunications, electricity, schools, hotels, recreation areas, public services, hospitals, worship centers, and the workforce. It is emphasized that the proximity of residential areas to industrial areas is

one of the important criteria requirements. Banks and other financial institutions close to the area provide sufficient capital flow for transactions and can offer the possibility to provide investment funds. On the other hand, nearby industries are critical for exchanging various resources, including materials, energy, treated wastewater, by-products, services, and training. In this sense, the distance of industrial facilities from existing industrial facilities, settlements, and city centers between 0-1000 m is considered appropriate (Sarapirome & Charunthanakij, 2012; Nuhu et al., 2022). Appropriate classification was made for the study area by considering these distances (Table 4; Fig 3).

2.2.3. Selection of Criteria for Agriculture Areas

A total of 26 criteria were used to determine suitable areas for agriculture, considering soil properties, topography, climate, and location. The criteria used to identify suitable areas were categorized according to their characteristics, and the degree of suitability was carefully selected based on literature sources, study area characteristics, and data availability (Table 5-6).

Table 5. Criteria and standards for the sub-criteria used in the analysis of land suitability for industrial areas

Soil Chemical Properties	Soil Physical Properties	Topographic and Climate Features	Water and Ecosystem Factors	Accessibility and Infrastructure Factors
Cation Exchange Capacity (a1)	Clay Content (b1)	Elevation (c1)	Distance to Water Resources (River, Lake) (d1)	Distance to Main Roads (e1)
Soil Organic Carbon (a2)	Bulk Density (b2)	Slope (c2)	Distance to Protected Areas (d2)	Distance to Railway (e2)
Soil pH (a3)	Sand (b3)	Soil Type (c3)	Distance to Agricultural Irrigation Infrastructure (d3)	Distance to Ports (e3)
Nitrogen (4)	Silt (b4)	Soil Moisture (c4)	Vegetation Density (d4)	Distance to Power Lines (e4)
	Volumetric Water Content at -33 kPa (b5)	Average Temperature (c5)	Distance to Existing Agricultural Areas (d5)	Distance to City Centers (Market, Input, Labor Access) (e5)
		Average Precipitation (c6)		
		Snow Depth (c7)		

Soil properties are one of the most important factors for determining areas suitable for agriculture. In many studies, criteria related to chemical and physical properties of soil have been examined (Akıncı et al., 2013; Montgomery et al., 2016; Tashayo et al., 2020). In this study, criteria related to soil properties, topography, and climate were emphasized to determine the areas suitable for agriculture. Soil cation exchange capacity (CEC), soil carbon content (SOC), soil pH, and nitrogen values, which are classified as soil chemical properties, are important. CEC is a critical criterion that shows the potential of the soil to retain nutrients and provide them to the plant when necessary, depending on factors such as the amount of clay minerals and organic matter. Soils with high CEC values increase productivity by reducing the losses of important nutrients such as calcium (Ca), magnesium (Mg), and potassium (K) (Van Erp et al., 2001; Yunan et al., 2018). SOC is the carbon contained in soil organic matter. It forms the basis of sustainable agriculture by strengthening plant nutrient cycling, soil structure, and water retention capacity. It also contributes to mitigating the effects of climate change by storing carbon (Chan, 2008). Soil pH is a critical indicator of the level of acidity or alkalinity of the soil and is at the basis of chemical and biological processes. This value significantly impacts microbial diversity, enzyme activities, and nutrient cycling, ultimately shaping crop yield and sustainability. The ideal range of soil pH is generally considered to be above 5.5 (Li et al., 2020). Nitrogen is an essential nutrient for food security and efficient agricultural production. However, its excessive or uncontrolled use can lead to environmental problems such as nitrate pollution in groundwater, increased greenhouse gas emissions, and ecosystem degradation. Therefore, effective nitrogen management is critical

for both ensuring high crop yields and maintaining sustainability (Robertson & Vitousek, 2009; Zolekar & Bhagat, 2015). Clay content, bulk density, sand, silt, and Volumetric Water Content at -33 kPa were evaluated in soil physical properties. Clay, sandy, and silty soils as soil textures are important criteria for agriculture. Clay (2 μm and below), silt (2-50 μm), and sand (over 50 μm) fractions in the soil are the main textural elements that determine water-holding capacity, aeration, and nutrient retention. Clay plays a critical role in productivity with its high cation exchange capacity and ability to bind organic matter; silt retains moderate water and is easy to work. Sand improves drainage and aeration but has a low nutrient retention capacity. The clay-silt-sand ratio of the soil directly affects the choice of cropping pattern and productivity. Moderate levels of bulk density, sand, and silt are considered optimal for agricultural soils as they ensure a balance between water retention, aeration, and root penetration. Excessively high or low values in these properties can negatively affect soil structure and crop productivity (Newman, 1984; Van Erp et al., 2001; McLauchlan, 2006; Brady & Weil, 2008; Colazo and Buschiazzi, 2015) (Table 6; Figure 3).

Topographical and climatic characteristics are also effective in agriculture. Land elevation, slope, soil type, and soil moisture content are among the criteria used in many studies. The elevation and slope values of the land are of vital importance. The distribution of soil properties, such as soil depth, moisture, texture, and nutrient availability, varies according to slope values (Datye and Gupte, 1984). The thickness of the soil layer decreases as the slope increases and increases as the slope decreases (Atalay, 2006). The amount of material transported by erosion increases as the degree of slope increases. Accordingly, the development of soil becomes slower with the increase in the degree of slope (Atalay, 2006), and soil depth and productivity decrease. On the one hand, slope indirectly limits agricultural production by negatively affecting soil properties; on the other hand, it directly affects agricultural production negatively by limiting the use of machinery and management practices such as tillage, irrigation, and drainage (Akıncı et al., 2013; Zolekar & Bhagat, 2015). Therefore, flat and low-lying areas are important for agriculture. Soil type has been created to help predict the conditions under which soils are formed and the behavior of soils. Soil behavior helps to predict soil performance for agricultural production. Soil moisture is a good indicator of soil quality and has a positive relationship with crop yield. Therefore, when deciding on the suitability of land for agricultural production, the dominant soil class and soil moisture content should be known (Akıncı et al., 2013; Zolekar & Bhagat, 2015). In agriculture, average climatic conditions and especially snow depths on the land for water accumulation are important for productivity. Accordingly, average precipitation, temperature, and snow depth are effective in the process of growing and ripening crops (Doorenbos and Kassam, 1979). Another important main condition for agriculture is the water and ecosystem factor. This primary factor evaluated distance to water sources, protected areas, agricultural irrigation infrastructure, vegetation density, and distance to existing agricultural areas. Distance to water sources and groundwater availability are vital for the sustainability of agriculture. Agricultural areas are both productive and sustainable in areas with less dense protected areas and vegetation cover. Agricultural areas suitable for agricultural cooperation should be close to existing agricultural areas (Reshmidevi et al., 2009; Yalew et al., 2016; Bozdağ et al., 2016). The last main factor to be evaluated for agricultural areas is accessibility and infrastructure features. Transport networks and energy infrastructure must be strong for agricultural areas to develop sustainably. In addition, it should be close to urban areas for labor, market, and raw material supply (Yalew et al., 2016; Montgomery et al., 2016; AL-Taani et al., 2021). In line with the information provided for each criterion above, their suitability according to the study area was determined (Table 6; Figure 3).

Table 6. Criteria and standards for the sub-criteria used in the analysis of land suitability for agriculture areas

Main Criteria	Sub-Criteria	Unsuitable	Low suitability	Medium suitability	High suitability	Very high suitability	Reference
Soil Chemical Properties	Cation Exchange Capacity	<180 mmol(c)/kg	180-210 mmol(c)/kg	210-235 mmol(c)/kg	235-270 mmol(c)/kg	>270 mmol(c)/kg	Van Erp et al., 2001; Yunan et al., 2018
	Soil Organic Carbon	< 0 dg/kg	0-170 dg/kg	170-230 dg/kg	230-350 dg/kg	> 350 dg/kg	Chan, 2008
	Soil pH	< 55 pH ×10	55-60 pH ×10	60-63 pH ×10	63-67 pH ×10	> 67 pH ×10	Li et al., 2020
	Nitrogen	<110 cg/kg	110-130 cg/kg	130-150 cg/kg	150-180 cg/kg	>180 cg/kg	Robertson and Vitousek 2009; Zolekar and Bhagat 2015
Soil Physical Properties	Clay Content	<180 g/kg	180-240 g/kg	360-420 g/kg	300-360 g/kg	240-300 g/kg	Brady and Weil, 2008
	Bulk Density	145 – 150 cg/cm ³	135 – 145 cg/cm ³	120 – 135 cg/cm ³	110 – 120 cg/cm ³	<110 cg/cm ³	Brady and Weil, 2008;
	Sand	>250 g/kg	250-320 g/kg	450-540 g/kg	390-450 g/kg	320-390 g/kg	Brady and Weil, 2008; Colazo and Buschiazzo, 2015
	Silt	>260 g/kg	260-310 g/kg	400-430 g/kg	370-400 g/kg	310-370 g/kg	Brady and Weil, 2008; Colazo and Buschiazzo, 2015
	Volumetric Water Content at -33 kPa	>270 10-2 cm3 cm-3	270-290 10-2 cm3 cm-3	290-310 10-2 cm3 cm-3	310-340 10-2 cm3 cm-3	<340 10-2 cm3 cm-3	Hillel, 2004
Topographic and Climate Features	Elevation	>700m	600-700m	500-600m	200-500m	<200m	Atalay, 2006; Bozdağ et all., 2016
	Slope	>15	8-15°	5-8°	2-5°	<2°	Datye and Gupte, 1984; Atalay, 2006
	Soil Type	Water Surfaces; High Mountain Grassland Soils	Rendzinas; Vertisol; Colluvial Hydromorphic Soils	Forest Soils; Reddish Brown Soils;	Non-Calcareous Brown Soils	Alluvial Soils	Expert
	Soil Moisture	<92mm	92-110mm	110-130mm	130-150mm	>150mm	Expert
	Average Temperature	<11°C	11.1-12 °C	15.6-17°C	14.1-15.5°C	12.1-14°C	Doorenbos and Kassam, 1979
	Average Precipitation	<1800 mm	1800-1900 mm	1900-2050 mm	2050-2255 mm	>2250 mm	Doorenbos and Kassam, 1979
	Snow Depth	<0.8 mm	0.81-1.8 mm	>4.61mm	2.91-4.60 mm	1.81-2.9 mm	Hatfield and Prueger, 2015
	Distance to Water Resources (River, Lake)	> 5000 m	3000-5000 m	1500-3000 m	500-1500 m	< 500 m	Reshmidevi et al., 2009; Yalew et al., 2016; Bozdağ et al., 2016; Expert
	Distance to Protected Areas	< 500 m	500-1500 m	1500-3000 m	3000-5000 m	> 5000 m	Reshmidevi et al., 2009; Yalew et al., 2016; Bozdağ et al., 2016; Expert
	Distance to Agricultural Irrigation Infrastructure	> 5000 m	3000-5000 m	1500-3000 m	500-1500 m	< 500 m	Reshmidevi et al., 2009; Yalew et al., 2016; Bozdağ et al., 2016; Expert
Water and Ecosystem Factors	Vegetation Density (NDVI)	> 0.32 (density)	0.25 – 0.31	0.19 – 0.24	0.10 – 0.18	< 0.10	Expert
	Distance to Existing Agricultural Areas	> 5000 m	3000-5000 m	1500-3000 m	500-1500 m	< 500 m	Expert

Accessibility and Infrastructure Factors	Distance to Main Roads	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	Yalew et al., 2016; Montgomery et al., 2016; AL-Taani et al., 2021; Expert Yalew et al., 2016; Montgomery et al., 2016; AL-Taani et al., 2021; Expert Yalew et al., 2016; Montgomery et al., 2016; AL-Taani et al., 2021; Expert Yalew et al., 2016; Montgomery et al., 2016; AL-Taani et al., 2021; Expert Yalew et al., 2016; Montgomery et al., 2016; AL-Taani et al., 2021; Expert
	Distance to Railway	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	
	Distance to Ports	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	
	Distance to Power Lines	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	
	Distance to City Centers (Market, Input, Labor Access)	>2000m	1500-2000m	1200-1500m	1000-1200m	<1000m	

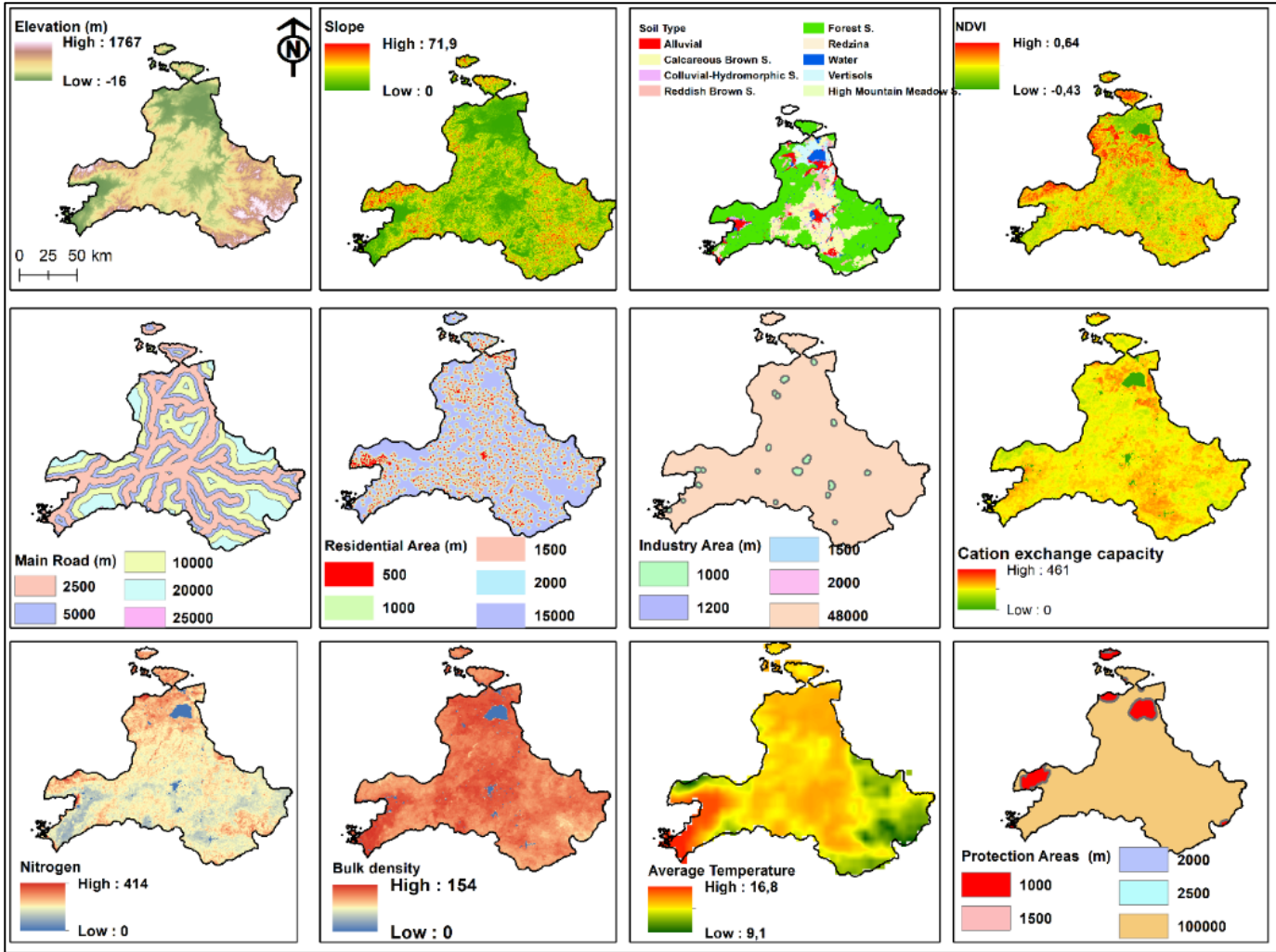


Figure 3. Spatial distribution maps of 12 sample criteria selected from the overall land suitability analysis.

2.3. Bayesian best-worst method and RPM

In this study, the Bayesian BWM method was employed to weigh the criteria. The binary comparison structure of traditional BWM is preserved, but it has been transformed into a

probabilistic structure to model preference differences among decision-makers and express uncertainty. Bayesian BWM addresses the relationships between criteria using a hierarchical modelling approach. Each decision-maker's preferences are based on a distribution model, and standard weights are derived from these distributions. This reduces the impact of inconsistencies and more reliably reflects the general trend of expert opinions (Mohammadi & Rezaei, 2020).

After the weights were obtained, the RPM method was used to rank the alternatives. RPM directly evaluates the suitability ratios of the criteria through the exponentiation product of global weights without requiring normalization. In this way, a single score is produced for each alternative. In other words, the basis of RPM involves multiplying the performance level of each alternative in each criterion by the weight associated with that criterion and taking the geometric mean of these product values. In this respect, it provides a more balanced scoring by mitigating the impact of extremely large or small weights on the result (Mohammadi & Rezaei, 2023). Within the scope of the study, the RPM ranking method was applied to the suitability classes determined for settlement, industry, and agriculture, and a ranking was performed for the most suitable class.

3. Application Result

3.1. Bayesian BWM results

In line with the Bayesian BWM method, the experts filled out questionnaires for residential, industrial, and agricultural land classes, and the weight values were calculated using MATLAB software.

3.1.1. Areas suitable for settlement

For settlement suitability analyses, 11 questionnaires were applied to the team of different fields, such as geography, emergency disaster management, industrial engineering, and urban planning. The survey results were evaluated, and weight values were calculated (Table 7).

Table 7. Weight Values Calculated for Areas Suitable for Settlement

Criteria Number	Global Weight	Criteria Number	Global Weight	Criteria Number	Global Weight
A1	0.1886	B2	0.2032	C3	0.0810
A2	0.1542	B3	0.0679	C4	0.1818
A3	0.0630	B4	0.1823	C5	0.3592
A4	0.1378	B5	0.1495	D1	0.0986
A5	0.2740	B6	0.2681	D2	0.1040
A6	0.1822	C1	0.1073	D3	0.5660
B1	0.1287	C2	0.2704	D4	0.2311

According to the survey results completed by experts, the criterion 'Ease of Access to Services (School, Hospital, Park-Garden, Bank, Theatre, Restaurant, etc.) (d3)' emerged as the most important criterion with a value of 0.5660 for the most suitable location for settlement. This criterion is followed by the 'Distance to Health Centers (State Hospitals and Large Private Hospitals) (c5)' criterion with a weight value of 0.3592. The least important criterion was the Aspect (a3) criterion with a value of 0.0630 and the Distance to Environmental Protection Areas (b3) criterion with a value of 0.0679 (Table 7). Using the credal ranking feature of Bayesian BWM, credal ranking graphs were first generated for all main criteria, followed by those for all sub-criteria. Figure 4 shows the credal ranking graph indicating the confidence level at which the criteria are superior to each other. The value on the arrow from one criterion to another varies between 0.5 and 1, with one indicating that the relevant criterion is superior. The credal ranking in this graph is represented by directional arrows indicating the level of confidence at which one criterion is superior to another. Each arrow indicates that the criterion at the starting point is more dominant than the criterion at the

endpoint and specifies the level of confidence at which this superiority exists (e.g., 0.93, 0.84, 1). For example, criterion a5 from group a is superior to both a1 and a6 with high confidence levels of 0.97 and 0.98, indicating that a5 is the most dominant criterion in the subgroup. Similarly, in group b, b6 has a high level of superiority over b2 and b4 with values such as 0.92 and 0.97. These graphs provide decision-makers with the opportunity to see not only the weight values, but also which criterion has a decisive superiority over which criteria under uncertainty. Thus, a more reliable inference power that takes epistemic uncertainties into account is added to the analysis process. This graph is shown here only for suitable settlement areas so as not to disrupt the flow of the article. The credal ranking diagram in Figure 4 serves as a representative methodological model that illustrates the study's conceptual framework and how epistemic uncertainties are managed within the network. The accuracy of the weight values has been demonstrated by applying this visualized validation process directly to other land-use types (industry and agriculture). However, to keep the article's visual density under control and avoid repetition, these ranking results for other classes have been directly incorporated into the final weighting tables as numerical data.

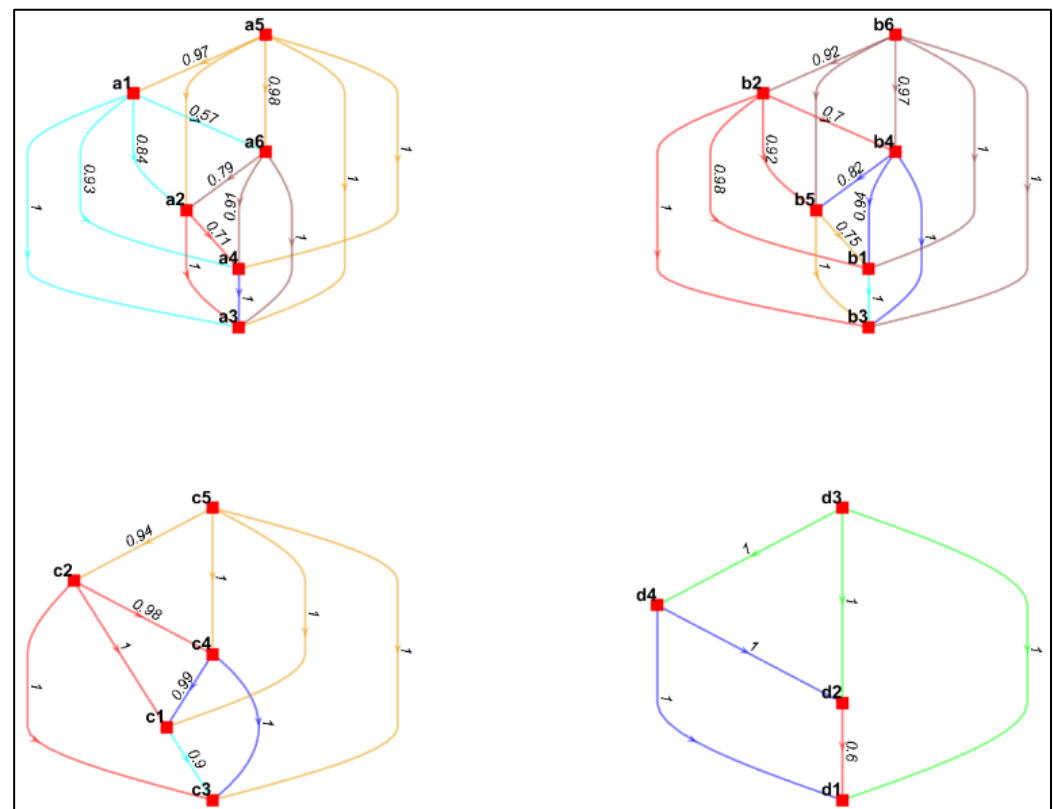


Figure 4. Credal ranking graph

The global weight values were calculated using MATLAB software, considering the survey results obtained. The weight values determined for each criterion were transferred to ArcGIS software, and an overlay analysis was performed using the Sum Weight tool. As a result of the overlay analysis, a suitability map for settlement was obtained.

Figure 5 shows the areas suitable for settlement in the province of Balıkesir. Accordingly, areas close to centers that are part of social life, such as schools, hospitals, banks, and theatres, which are prominent for settlement areas, have been classified as suitable areas. The fault lines located in Balıkesir, and its surroundings are also important for settlement areas, and areas far from the fault line have been evaluated as suitable areas. Additionally, areas close to the existing road network, with lower forest density, proximity

to industrial centers, and ideal elevation and slope values have been classified as suitable areas for settlement.

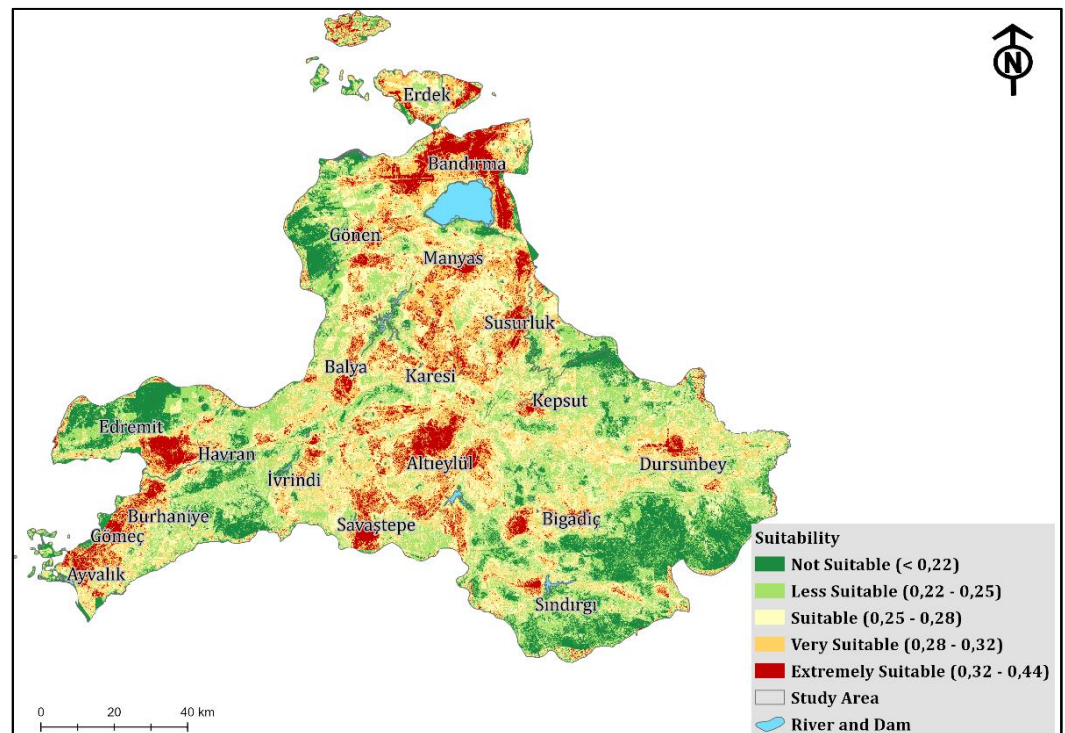


Figure 5. Final suitability map for settlement area in the Balıkesir

Areas particularly suitable for settlement include the vicinity of Bandırma district, the areas east and northeast of Manyas Kuşgölü, and regions close to the coastal area between Edremit and Ayvalık, which stand out as the most suitable areas. Altıeylül (Balıkesir's provincial center), Savaştepe, Susurluk, and Manyas district centers, along with their suitable surrounding areas, stand out as suitable areas for settlement. Criteria such as the presence of centers that are part of social life, such as hospitals, schools, and banks, their location on transport networks, and ideal elevation and slope have been effective in these regions (Figure 5).

3.1.2. Areas Suitable for Industrial Areas

The procedures carried out for the settlement area were also performed to calculate areas suitable for industry. Table 8 shows the calculated global weight values. Accordingly, the most important criteria were, in order, Distance to Energy Transmission Lines (c5: 0.1322), Proximity to Ports (c3: 0.1322), and Distance to Main Road Network (c1: 0.1042). The least important criterion was Aspect (a3) with a value of 0.0121, followed by Distance to Health Centers (d4) with a value of 0.0137. It is noteworthy that, although health centers should be important for industrial areas, users considered them less important than other criteria.

As in the settlement suitability analysis in Figure 6, areas suitable for industrial zones in Balıkesir Province are indicated. On the map, red colors indicate 'highly suitable' areas, while dark green areas indicate 'areas unsuitable for industry'. Accordingly, areas suitable for industry are generally located in regions with dense transport networks, plains and flatlands with minimal elevation and rugged terrain, areas close to the coast and therefore near ports, and areas crossed by energy transmission lines. In particular, the central area of Balıkesir (around Karesi and Altıeylül), Bandırma, Gönen, Gökçe, Ayvalık, and Susurluk districts stand out as the most suitable areas for industry. These regions are well connected by road and rail, as well as port, and are advantageous in terms of agricultural production, labor force, and proximity to markets.

Table 8. Weight values calculated for areas suitable for industrial areas

Criteria Number	Global Weight	Criteria Number	Global Weight
A1	0.0327	C1	0.1043
A2	0.0596	C2	0.0571
A3	0.0121	C3	0.1322
A4	0.0580	C4	0.0377
B1	0.0595	C5	0.1383
B2	0.0460	D1	0.0281
B3	0.0527	D2	0.0204
B4	0.0616	D3	0.0240
B5	0.0620	D4	0.0137

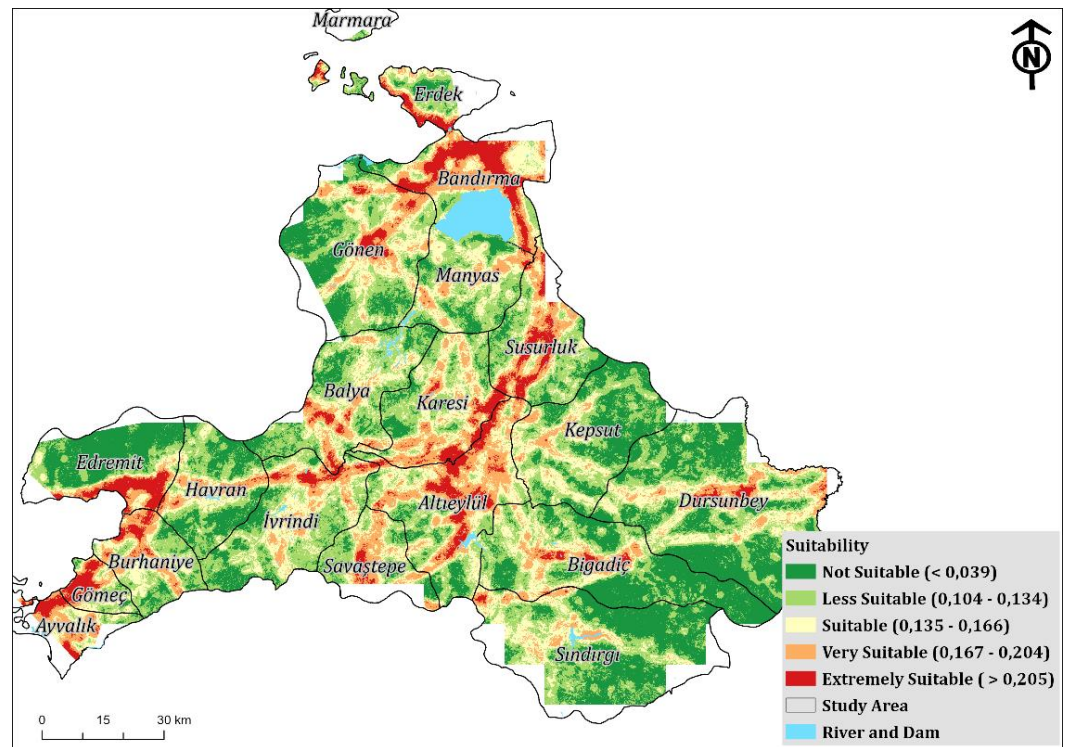


Figure 6. Final suitability map for industrial area in the Balıkesir

In terms of suitability for industry, the Bandırma and Gönen areas in the north of Balıkesir are noteworthy. Bandırma is well-suited for port trade due to its location on the coast of the Sea of Marmara and its strategic position, thanks to its proximity to Istanbul and Bursa, as well as favorable land conditions and transport links. This provides significant logistical advantages for industrial development. The Gönen and Susurluk corridor also offers suitable areas for industrial investment, with both road access and agricultural production potential. The concentration of these areas in red and orange tones on the map confirms their suitability for industry (Figure. 6).

Although certain areas along the Ayvalık, Burhaniye, and Edremit coastlines in the west and southwest are considered suitable, these regions are characterized by intensive tourism, olive cultivation, and agricultural activities. Consequently, industrial development in these areas may be restricted; particularly, the Ayvalık and Cunda areas will not be suitable for industrial zones due to environmental values and tourism pressure. On the other hand, it is noteworthy that suitable areas exist in the inland regions, such as around İvrindi and Balya. These areas have the potential for industrial activities due to their natural resources and mineral potential (Figure. 6).

Looking towards the east and southeast, it is seen that green and dark green tones prevail in districts such as Bigadiç, Sındırgı, and Dursunbey. This suggests that the

mountainous, forested, and rural character of these areas is not conducive to industry. However, the presence of red tones around Bigadiç points to potential, particularly for the mining industry. In conclusion, the map indicates that industrial investments in Balıkesir are likely to be concentrated in the central, northern, and northeastern districts. At the same time, rural and mountainous areas have limited potential for industrial development (Figure 6).

3.1.3. Areas suitable for agriculture areas

The procedures carried out for settlement and industrial suitability areas were also performed to determine areas suitable for agriculture. Table 9 shows the calculated global weight values. According to the table, the criterion with the highest weight value in terms of agricultural suitability is C& (average rainfall, 0.1315). This reveals that rainfall plays a crucial role in agricultural production, particularly under specific climatic conditions. Furthermore, the high weight values of criteria such as D1 (distance to water sources, 0.1145) and C4 (soil moisture, 0.0769) indicate that water and moisture factors are also critical for agricultural productivity. On the other hand, it is noteworthy that the criteria with the lowest weight values are E2 (distance to railways, 0.0052) and E4 (distance to power lines, 0.0057). This shows that transportation and infrastructure factors are of secondary importance for agricultural production compared to industry. In conclusion, these prioritizations obtained from the surveys indicate that climate and water factors are fundamental in determining agricultural areas, while infrastructure factors are complementary in nature (Table 9).

Table 9. Weight values calculated for areas suitable for agriculture areas

Criteria Number	Global Weight	Criteria Number	Global Weight	Criteria Number	Global Weight
A1	0.0081	C1	0.0292	D3	0.0601
A2	0.0168	C2	0.0359	D4	0.0349
A3	0.0594	C3	0.0415	D5	0.0306
A4	0.0342	C4	0.0769	E1	0.0145
B1	0.0276	C5	0.0620	E2	0.0052
B2	0.0280	C6	0.1315	E3	0.0102
B3	0.0119	C7	0.0217	E4	0.0057
B4	0.0155	D1	0.1145	E5	0.0275
B5	0.0820	D2	0.0148		

Figure 7 shows the areas suitable for agriculture in Balıkesir province. Here, the red tones indicate areas that are 'extremely suitable' for agriculture, while the dark green colors represent 'unsuitable' areas. Agricultural activities are concentrated in flat areas, near rivers and lakes, and on plains with fertile soil. The predominance of red and orange colors, particularly around Manyas, Gönen, Balya, and Susurluk, reveals that this region is the most suitable for agriculture in terms of climate, water, and soil characteristics. The Bandırma-Manyas-Gönen line in the north is particularly noteworthy. The area around Lake Manyas is highly advantageous for agriculture due to its proximity to water sources and fertile alluvial soils. Similarly, the Gönen plain and the area around Susurluk are considered highly suitable for agriculture due to both climatic conditions and irrigation possibilities. The intensity of the red tones here indicates high agricultural potential. The areas around Edremit, Burhaniye, Gömeç, and Ayvalık in the west are also highly suitable. These regions are particularly notable for their prominence in olive, vineyard, and vegetable production. However, in coastal areas, agricultural land may gradually diminish due to tourism pressure and construction. Inland, fertile areas are also found around İvrindi and Savaştepe.

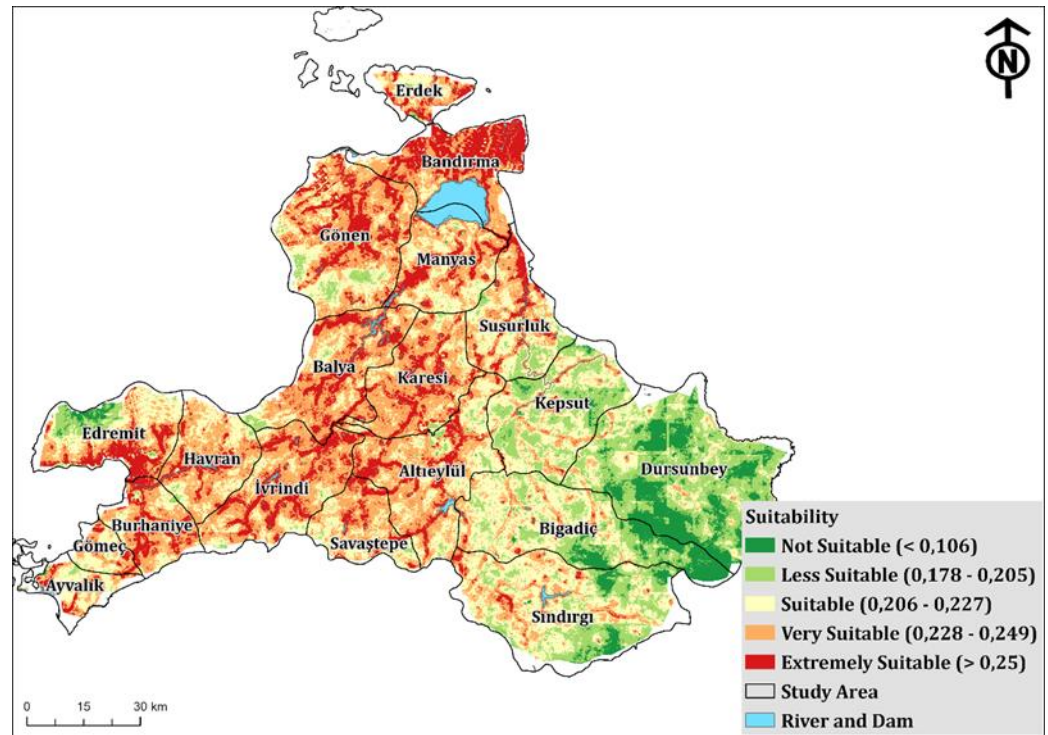


Figure 7. Final suitability map for agriculture area in the Balıkesir

Looking towards the east and southeast, it is observed that the Bigadiç, Sındırgı, and Dursunbey areas are dominated by greener tones, meaning that there are limited areas suitable for agriculture. The primary reason for this is that the region comprises mountainous, rugged, and forested areas. Nevertheless, valley floors and small plains provide opportunities for local agricultural production. Consequently, agricultural suitability in Balıkesir is concentrated mainly in the northern, western, and central districts, while agricultural activities are more limited in the eastern and southeastern parts due to natural conditions (Figure 7).

3.2. Determining the most suitable areas with RPM

At this stage, the RPM method was applied to determine the relative suitability of each class, based on the effects of numerous criteria used in suitability analyses. RPM is an effective ranking method that ranks decision alternatives (five classes for all analyses in this study) based on their internal weight scores, without the need for normalization. This model aims to obtain a total suitability score by multiplying the suitability score of each class by both the area and the global weight of the criterion (Mohammadi and Rezaei, 2023). The most suitable areas for each land use class were identified, and the ratio of the suitable area for each criterion to the total class area was calculated. This ratio was multiplied by the global weight of the relevant criterion, and this process was repeated for all criteria. As a result, an RPM score was obtained for each class. This calculation is performed using the formula proposed by Mohammadi & Rezaei (2023), as expressed in Equation 1:

$$RPM_j = \sum_{i=1}^n w_i \times r_{ij} \quad (1)$$

where:

RPM_j : j alternative's total suitability score,

w_i: i. the global weight of the criterion (calculated using Bayesian BWM),

r_{ij}: j. is the compliance ratio for criterion i. for class j (suitable area / total area).

Using this method, a meaningful suitability score has been calculated for each class, taking all criteria into account without the need for normalization.

3.2.1. RPM-based suitability classification for settlement areas

In this section, the RPM method was used to evaluate areas suitable for settlement. Considering the weight values of the 21 criteria previously determined using the Bayesian BWM method, the areas suitable for settlement above were classified into five classes. The fifth class, which was evaluated as the most suitable class out of these five classes, was divided into five parts within itself to calculate the RPM (the fifth class was divided into equal parts between 0.32 and 0.44). Then, the total area value was calculated for each class, and the most suitable area for each criterion (Table 2) was determined and compared to the total area of the class. These ratios were multiplied by the global weights of the relevant criteria to obtain weighted contributions. All weighted contributions obtained were summed to calculate the final RPM score for each class. This method allows for the simultaneous evaluation of multiple criteria, providing decision-makers with the opportunity to compare classes. Below is an example calculation table for a single class (Table 10).

Table 10. Calculation of RPM Scores for class 1 settlement suitability based on global weights

<i>1st Class</i> Criteria	Area (km ²)		Proportion of the Most Suitable Area (km ²)	Results Multiplication by Global Weights
	840.191.486 The Suitable (km ²)	Most Area		
Elevation	489,543.932		0.5826	0,9696
Slope	201,608.483		0.2399	0,9079
Aspect	371,372.061		0.4420	0,9559
Soil Type	331,966.281		0.3951	0,9601
Earthquake Risk (Distance to Fault Lines)	794,883.804		0.9460	0,9974
Geological	79,722.044		0.0948	0,8775
Distance to Stream	800,929.745		0.9532	0,9980
Distance to Lakes	373,277.842		0.4442	0,9620
Distance to Environmental Protection Areas	802,359.807		0.9549	0,9988
Average Precipitation	51,992.224		0.0618	0,9757
Average Temperature	208,923.523		0.2486	0,9884
Vegetation (NDVI)	422,759.943		0.5031	0,9867
Distance to Residential Areas	95,843.501		0.1140	0,9468
Distance to Main Road	639,097.041		0.7606	0,9948
Distance to Railway	164,515.007		0.1958	0,1958
Distance to Power Lines	295,058.673		0.3511	1,0000
Distance to Health Centers (State Hospitals and Large Private Hospitals)	113,577.382		0.1351	1,0000
Population Density (person)	174,878.179		0.2081	1,0000
Distance to Historical and Cultural Areas	243,460.732		0.2897	1,0000
Ease of Access to Services (School, Hospital, Park-Garden, Bank, Theatre, Restaurant etc.)	433,616.848		0.5160	1,0000
Distance to Industrial Facilities	17,010.768		0.0202	1,0000
RPM SCORE (TOTAL)				19,7154

The application of RPM has enabled prioritizing suitability classes by evaluating the criteria multiplicatively (Mohammadi & Rezaei, 2023). Within this framework, Class 4 has emerged as the most optimal and highest-priority area for settlement, outperforming the other classes. RPM inherently possesses a non-compensatory nature. In this sense, unlike traditional additive models that can mask critical weaknesses, RPM can actively exclude

areas with significant deficiencies in any key criterion via a 'veto effect' (Yoon & Hwang, 1995; Malczewski & Rinner, 2015). In multiplicative models, if any sub-criterion takes the value of zero, this resets the entire score to zero, creating an absolute veto effect. To prevent this mathematical issue, particularly when calculating 5th-class settlement areas, the zero values have been replaced with the constant epsilon ($\epsilon = 0.0001$). This value has been selected as a standard constant that is large enough to eliminate absolute zero, yet small enough not to disrupt the natural balance of the other factors in the model. By mathematically isolating areas with restrictive geographical or infrastructural constraints, this model has demonstrated that Class 4 offers the most balanced, consistent, and sustainable spatial profile. Consequently, this class is important for strategic urban planning, as it ensures that selected settlement sites are free of critical security vulnerabilities and possess an optimal combination of all necessary socio-economic and environmental conditions. Accordingly, the highest RPM score was 0.2750 (4th class), while the lowest was 0.1190 (1st class) (Table 11).

Table 11. RPM scores according to settlement suitability classes

Suitability Class	RPM Score
5th Class (Most Suitable)	0,2499
4th Class (Most Suitable)	0,2750
3rd Class	0,2444
2nd Class	0,2031
1st Class (Least Suitable)	0,1190

According to the suitability analysis based on RPM for the study area, the most suitable areas -represented by Class 4 settlement zones- are geographically concentrated, particularly around the north-eastern, south-western, and southern districts (Savaştepe). A balanced combination of low-lying, flat terrain, strong proximity to transport infrastructure, and high integration with existing settlement centers and service areas characterizes these areas. Highlighted in red on the suitability map, these areas represent the regions with the highest RPM scores and hold absolute priority potential for future settlements. The total area of these most suitable settlement areas (Class 4) identified within the scope of the study is approximately 12.52 km²; they stand out as the primary focus of the study due to the absence of critical limiting factors. (The spatial distribution of the other suitability classes is as follows: 1.22 km² for Class 5, 130.05 km² for Class 3, and 349.01 km² for Class 2). On the other hand, Class 1 settlement areas, indicating the least suitable areas, are shown in green on the map and are largely confined to the north-western coastal sections, to highly rugged terrain, and to regions significantly distant from settlement centers and service areas, compared to Class 4. The low RPM scores of these areas, which cover approximately 840.19 km², indicate that they are subject to significant spatial constraints and are therefore far less suitable for settlement. Consequently, the suitability ratings for settlement obtained using the RPM method provide a consistent spatial distribution that effectively accounts for restrictive criteria, thereby identifying suitable areas for settlement planning (Figure 8).

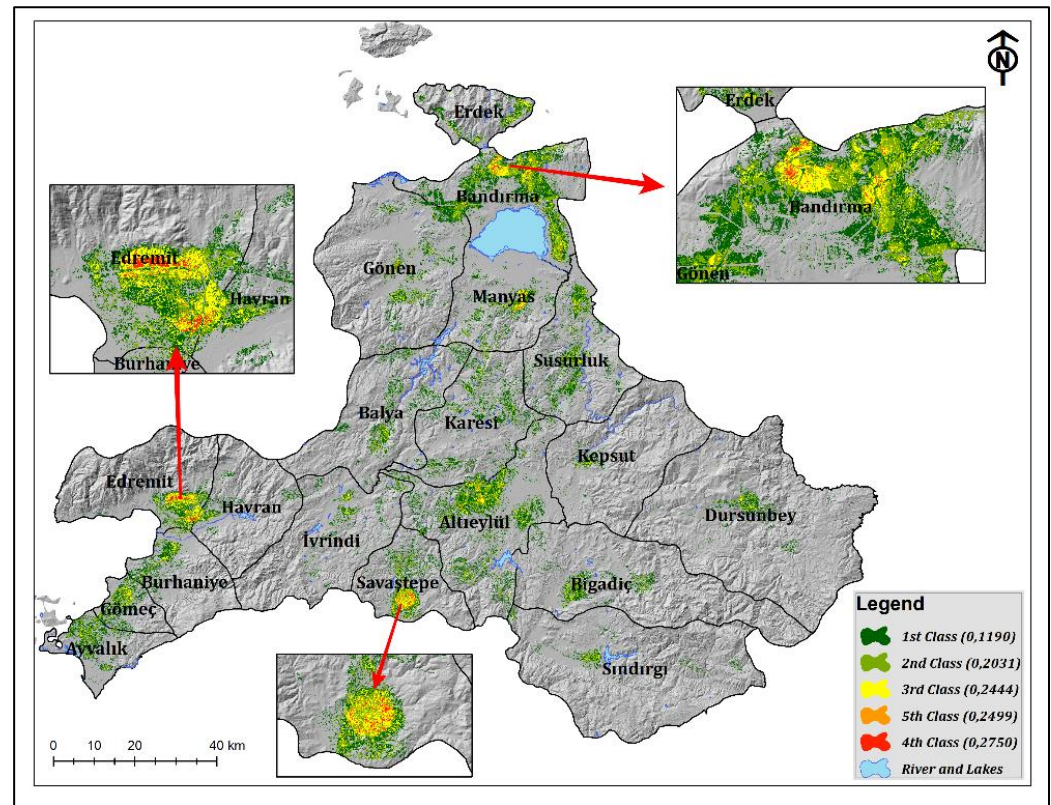


Figure 8. Classification of areas most suitable for settlement based on RPM scores

3.2.2. RPM-based suitability classification for industrial areas

The RPM model applied to industrial areas has been implemented in the same manner as it is applied in suitability analysis for settlement. All stages are identical. Based on the RPM scores obtained, the suitability of industrial areas was assessed, and the regions with the highest scores were identified as the most suitable areas. In this context, the regions with an RPM score of 0.6036 are considered the most suitable areas for industry, while those with a score of 0.1935 are classified as the least suitable areas (Table 12).

Table 12. RPM scores according to industrial suitability classes

Suitability Class	RPM Score
5th Class (Most Suitable)	0,6036
4th Class	0,5452
3rd Class	0,4159
2nd Class	0,2677
1st Class (Least Suitable)	0,1935

When examining Figure 10, the most suitable industrial areas (red zones) are located particularly around Bandırma, Gönen, Susurluk, Burhaniye, and Ayvalık. These areas offer infrastructure advantages, including proximity to ports, road and rail integration, and access to electricity lines. The Bandırma region has a high RPM score due to its strong logistics capabilities, including the Port of Bandırma and its road and rail connections (Figure 9). Similarly, the areas around Burhaniye and Ayvalık stand out due to their proximity to the Aegean coast, flat topography, and existing transport infrastructure. The areas around Susurluk are prominent because they are located on road transit routes and have favorable slope/topography conditions. The fact that these areas, which received high suitability scores from the model, correspond exactly with the existing active industrial facilities and industrial zones in Bandırma, as can be clearly seen in the satellite imagery, demonstrates the model's alignment with reality and its validity.

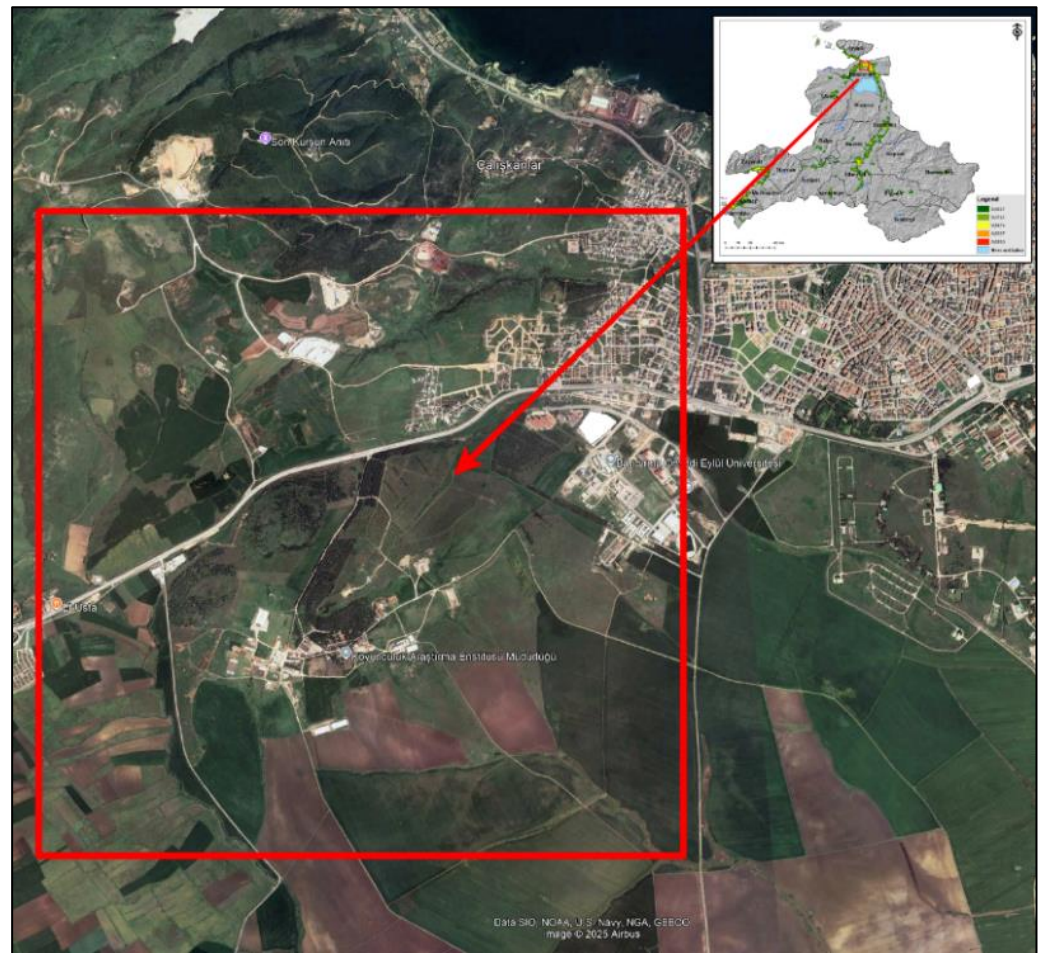


Figure 9. Model industrial estate in the Bandırma area (Area verification using satellite imagery)

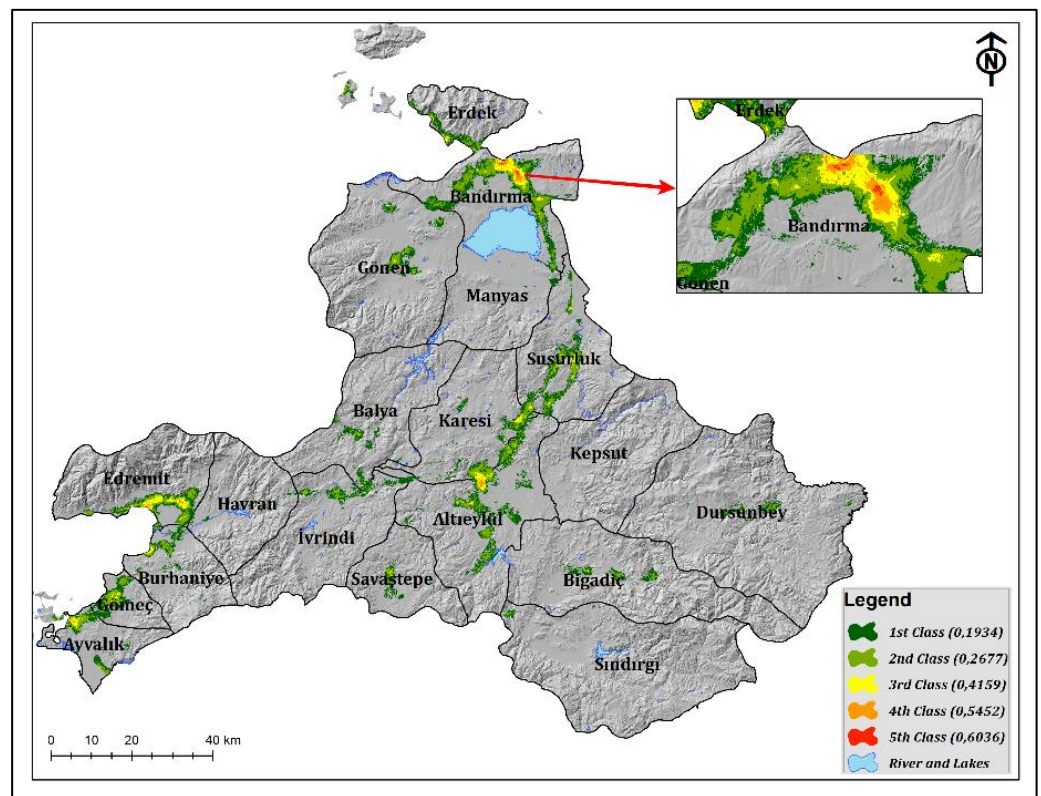


Figure 10. Classification of areas most suitable for industrial based on RPM scores

On the other hand, the areas shown in green, with low RPM scores, could serve as alternatives to areas with high RPM values. These areas are again concentrated around transport routes, in the hinterland of ports, and in partially sloping and elevated areas. Areas partially behind the coastline between Altıeylül-Susurluk and Edremit-Ayvalık are included in this category. Areas in eastern and southeastern districts, such as Sındırgı and Dursunbey, are also disadvantaged in terms of industrial investment compared to other regions. In conclusion, this RPM-based analysis reveals that factors such as infrastructure, transportation, topography, and current land use are crucial in planning industrial areas.

3.2.3. RPM-based suitability classification for agriculture areas

The assessment of suitability for agricultural areas was applied in the same manner as the methods used for residential and industrial areas. Within this scope, criterion weights were obtained using the Bayesian BWM method, considering the 26 criteria identified. Using these weights, RPM scores were calculated for each class (as in residential and industrial areas, the most suitable area for the RPM score was divided into five classes). The scores obtained were evaluated in 5 classes. Accordingly, the most suitable (5th class) RPM score for agricultural areas was determined to be 0.3868, while the score for the least suitable (1st class) area remained at 0.1102 (Table 13).

Table 13. RPM scores according to agriculture suitability classes

Suitability Class	RPM Score
5th Class (Most Suitable)	0,3868
4th Class	0,3111
3rd Class	0,1981
2nd Class	0,1381
1st Class (Least Suitable)	0,1102

According to the RPM analysis results, the most suitable area is the 5th class (0.5330) agricultural area, which constitutes the most advantageous region from an agricultural perspective. The 1st class region is located within the agricultural areas that can be considered as alternatives. According to Figure 11, most of the most suitable areas for agricultural activities are on the north and north-west belt. In particular, the areas in red and orange tones on the flat lands near the coast, around Gönen, Balya, Manyas, Edremit, Bandırma, Erdek, Havran, and Ayvalık, are of 4th and 5th class suitability (Figure 11). These regions generally have alluvial soils and are also favorable in terms of climatic conditions. Factors such as the influence of maritime humidity, a more regular rainfall regime, and the availability of water resources have contributed to the high RPM scores of these areas. Furthermore, the irrigation infrastructure and high groundwater levels in these areas have also had an increasing effect on suitability scores.

According to the results, Class 1 and Class 2 areas are concentrated in the more central regions, located behind the coastline, around İvrindi, Savaştepe, and Altıeylül. Although these areas are suitable for agriculture, they are preferable to Class 4 and Class 5 areas. These areas offer certain advantages, such as proximity to water sources, irrigation infrastructure, and acceptable slope and elevation values. In contrast, suitable areas are relatively limited along the Sındırgı, Dursunbey, and Bigadiç axis in the southeast of the study area. There are a few Class 1 and 2 areas in these regions. Therefore, these areas are disadvantaged for agricultural use. Factors such as high slopes, shallow soil depths, the prevalence of impermeable soil types, and distances from water sources limit their agricultural suitability. Furthermore, the climate in these regions is more continental, and annual rainfall amounts are lower compared to the north; this also contributes to low soil moisture levels (Figure 12).

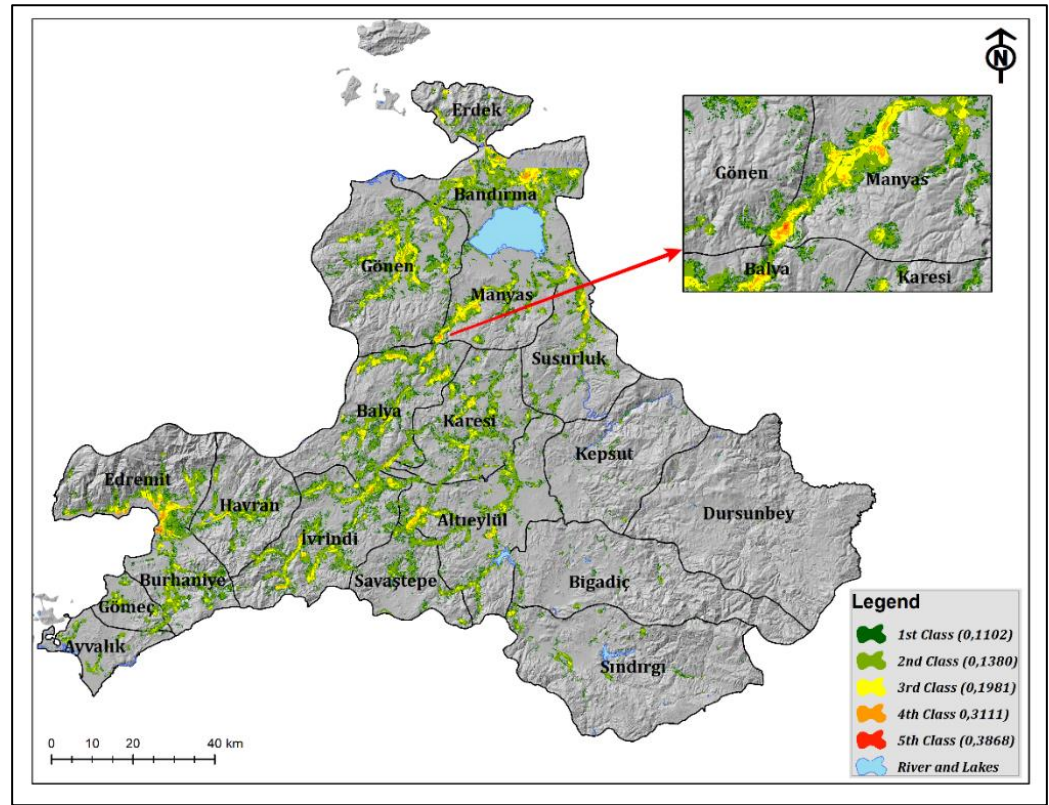


Figure 11. Classification of areas most suitable for agriculture based on RPM scores

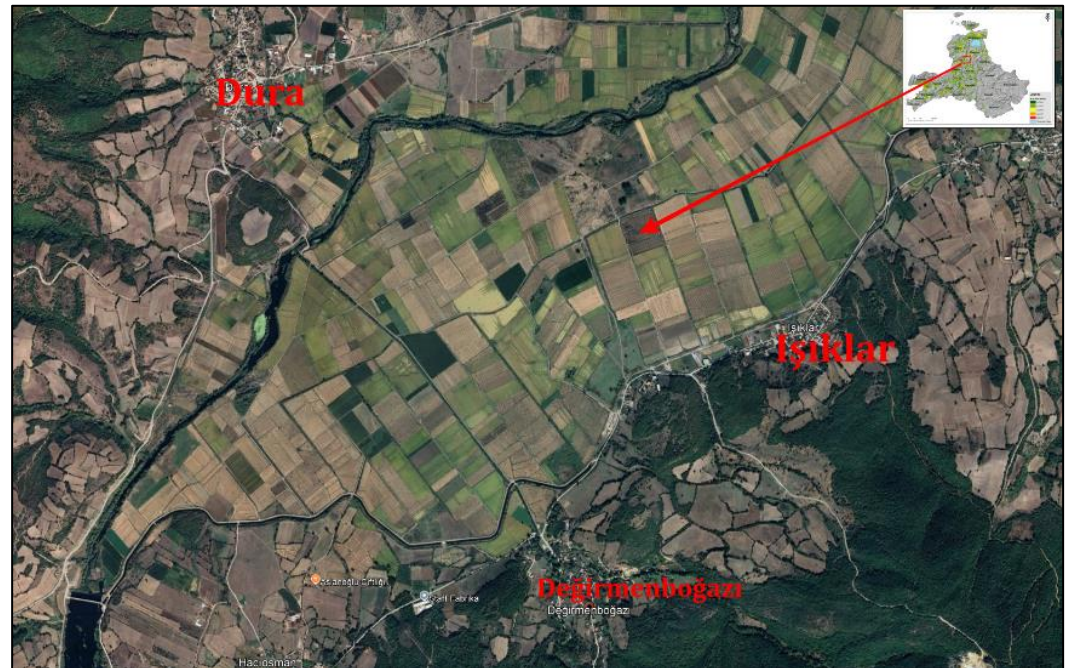


Figure 12. Suitable agriculture estate in the Manyas (Değirmenboğazı) area (Area verification using satellite imagery)

Consequently, the suitability map obtained using the RPM method exhibits a distribution consistent with the topographical, soil, and hydrogeological characteristics of the region. It is noted that plains and alluvial deposits stand out with high suitability scores. The satellite image verification presented in Figure 12 also supports this finding, confirming the reliability of the spatial analysis results by demonstrating that the areas identified by the

model as having high agricultural suitability correspond exactly with the existing fertile agricultural land around Manyas (Değirmenboğazi).

4. Discussion

This study utilized both Bayesian BWM and RPM methods to identify sustainable areas for different land use types (settlement, industry, and agriculture). The Bayesian BWM method offers more flexible and reliable weighting results compared to the classical BWM approach, thanks to its capacity to model decision-maker uncertainties. The identified criterion weights were considered separately for each land use type to perform suitability assessments. The RPM method was preferred for the suitability ranking due to its structure, which is sensitive to ranking preservation and does not require normalization, thus enabling comparison.

When compared to similar studies in literature, the diversity of methods used, and the consistency of results are evident. For example, Zolekar & Bhagat (2015) evaluated criteria such as soil, slope, and drainage using the AHP approach when conducting suitability analysis of agricultural areas in a hilly region in western India. The spatial distribution of the effects and suitability classes obtained shows that the weight of natural factors is decisive, like the agricultural lands in this study. However, in this study, the statistical inclusion of uncertainties in expert opinions, using Bayesian BWM in the model, allowed for healthier criterion weights. This approach resonates with earlier efforts published in Cartography and Geographic Information Science, such as Guan et al. (2005), who successfully integrated Artificial Neural Networks into Cellular Automata to reduce subjectivity in calibration. Following this trajectory of reducing subjectivity in GIS-based modeling, study employs a probabilistic approach to refine decision-maker inputs.

Another study, Foroozesh et al. (2022), evaluated urban development by integrating group fuzzy BWM, AHP, and TOPSIS methods with GIS. The study revealed that the most suitable areas for urban development were concentrated in regions with high levels of transportation and infrastructure facilities. Similarly, this study also found that the most suitable areas for settlement in the province of Balıkesir are concentrated in regions such as Bandırma, Gönen, Altıeylül, and Karesi, which are advantageous in terms of transportation, infrastructure, elevation, and slope. This demonstrates that, despite the different methods used, the influence of transportation and infrastructure criteria persists in spatial decision support applications.

Another study by Akıncı et al. (2013) emphasized the effect of physical variables, such as slope, soil, and current land use, in GIS-AHP-based agricultural suitability studies. The study showed that suitable areas were clustered in flat, alluvial areas close to irrigation facilities. Similarly, in this study, flat areas and alluvial sites with low elevation and slopes adjacent to lake and river networks were classified as suitable areas for agriculture. Consequently, both studies confirm the determining role of climate and water-soil components. However, this study also ensures that the RPM's multiplier structure clearly and consistently categorizes flat areas near water in Balıkesir as 'highly suitable'. In the suitability analysis for industrial areas, Midatana et al. (2018) considered criteria such as transport, proximity to water sources, and topographic structure to identify suitable areas for industrial investment in India. This study also considered similar criteria, which emerged as key factors in the results.

In summary, the Bayesian BWM-RPM integrated approach used in this study makes a significant contribution to spatial decision support systems. A weighting process that accounts for uncertainties in expert opinion has been integrated into a ranking method based on direct comparison. Brief comparisons with similar studies in the literature demonstrate the consistency of the methodology and application results of the method used.

Although aggregate models such as traditional GIS-based weighted land-use classification (WLC) are frequently preferred in spatial planning, they have a compensatory

structure in which other high-scoring criteria offset low-scoring weak criteria. This situation can lead to the concealment of potential spatial risks. In contrast, multiplicative models such as RPM, which are integrated in this study, do not tolerate major weaknesses in any criterion (non-compensatory) and can thus make risks much more clearly visible. The findings indicate that, unlike additive models, RPM can prevent erroneous site selections that are difficult to rectify, thereby offering a much safer and more constraint-sensitive decision-support mechanism for spatial decision-makers and planners.

Although the proposed methodological framework provides a tool for spatial planning, certain limitations must be considered. Firstly, whilst the division of the 'most suitable' (Class 5) category into sub-groups within the RPM application is effective for determining application priorities within areas, this involves a degree of methodological generalization, and the final maps may be sensitive to the structure of these classification intervals. Secondly, although inter-expert uncertainties were successfully modeled in this study using Credal ranking and Bayesian BWM, a traditional sensitivity analysis—where criterion weights are manually adjusted—was not conducted. Similarly, the confidence intervals associated with the Bayesian BWM weights have not been directly incorporated as an uncertainty-propagation layer in the final spatial maps. This presents significant potential for future studies to model the spatial propagation of uncertainty. Finally, in the context of model validation, as detailed in Figures 9 and 12, it has been confirmed that the model's high-fit areas align consistently with existing active industrial and agricultural zones using high-resolution satellite imagery.

5. Conclusions

In this study, three different land use suitability categories -settlement, industry, and agriculture- were weighted using Bayesian BWM for the province of Balıkesir, and suitability maps were generated in a GIS environment using these weights. Subsequently, the classes determined using the RPM method were prioritized. Subsequently, RPM was applied to divide the 'most suitable' class (5th class) into equal subgroups within itself, and a single score was obtained by multiplying the global weight values to maintain the ranking. Thus, not only the suitability distribution but also the application priority was determined and concretized.

According to the output results, the criteria for ease of access to services' (d3) and 'distance to health centers' (c5) were the most decisive for suitable settlement areas. According to the results, the density of suitable areas has increased in regions close to service centers and transport networks, with favorable slope and elevation conditions. Bandırma, its surroundings, the east-north of Manyas Kuşgölü, Altıeylül center, and Susurluk stand out. Areas distant from fault lines, close to the road network, and with low forest density have been classified as suitable for settlement.

In the study area, the criteria of distance to energy transmission lines for industrial areas (c5), proximity to ports (c3), and proximity to the leading road network (c1) were assigned high weight values, while the criterion of distance to care and health centers was assigned relatively lower weight values. In terms of suitability, the Karesi-Altıeylül center, the Bandırma-Gönen-Susurluk line, and the Gömeç-Ayvalık area stand out as regions with dense transport networks and suitable access to the coast and ports. There are fewer areas suitable for settlement in the mountainous and forested eastern and south-eastern districts (Bigadiç, Sındırgı, Dursunbey). The analysis conducted using RPM prioritized regions with the strongest simultaneous access to the port-energy-road triad, classifying the Bandırma logistics gateway and the Gönen-Susurluk corridor as the most priority areas.

In the suitability classification for agricultural areas, climate-water criteria such as average rainfall (c6), distance from water sources (d1), and soil moisture (c4) were found to be decisive factors, while transport/infrastructure variables (railway, power lines, roads, etc.) were of secondary importance. According to the results, areas suitable for agriculture

are concentrated in the alluvial-based, water-proximal, flat areas along the Manyas-Gönen-Balya-Susurluk line. Significant suitability values were also identified along the Edremit-Burhaniye-Gömeç-Ayvalık coast. Large-scale agricultural suitability is more limited in the east and southeast of the study area (Bigadiç, Sındırgı, Dursunbey). According to the RPM score results, the areas around Lake Manyas and the Gönen Plain are the most suitable for agriculture, particularly within the most suitable class.

In general, the integrated use of Bayesian-BWM and GIS reveals which criteria are strong. At the same time, RPM has produced an application priority that directly answers the question of 'where to start' within this suitability pool. Although high suitability clusters in settlement, industry, and agriculture classifications differ spatially, concentration has been observed in areas with strong transport/logistics access and favorable soil-water composition. Unlike deterministic methods, the probabilistic nature of Bayesian BWM enhances the transparency and reliability of the spatial decision-making process by modeling uncertainty rather than ignoring it. The production of maps should be updated and integrated to reflect changes over time, such as the addition of new roads/OSB facilities, irrigation facilities, and precipitation-temperature trends. Finally, incorporating environmental-social factors, such as disaster-prone areas and habitat continuity, as filters in the RPM ranking will enable the selection of not only the most suitable but also the least conflict-prone areas.

The findings of this study provide directly applicable outcomes for local authorities and urban planners in Balıkesir. The maps produced can be used as a strategic decision-support tool to direct future industrial growth towards the Bandırma-Susurluk corridor, protect productive agricultural basins such as Manyas and Gönen from development pressure, and allocate limited public resources (infrastructure and service investments) to the most appropriate and low-risk areas.

Ethics approval and consent to participate: This study does not involve any experiments on human or animal subjects. Informational consent was obtained from all experts who participated in the survey process used for criteria weighting.

Author Contributions: The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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AI Contribution Statement: Generative AI tools (Claude Opus 4.8) were used solely to assist in the visual design of the methodological flowchart (Figure 1). All scientific workflows, criteria, and interpretations represented in the flowchart were reviewed, controlled, and approved by the author.

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Conflicts of Interest: The author declares no conflicts of interest.

Data Availability: The minimum data and materials required to reproduce this study have been shared in a Zenodo repository under a CC BY 4.0 license: <https://doi.org/10.5281/zenodo.17542789>. The repository contains only (i) the Bayesian BWM survey form and the final criterion weights (Excel file), and (ii) a sample ArcGIS project prepared to illustrate the workflow, including a representative subset of raster and vector data used in the settlement suitability analysis along with the project file. Due to large file size constraints (in the gigabyte range), all raw GIS layers and comprehensive intermediate outputs have not been uploaded to the repository. The summary values underlying the figures and tables presented in the article can be reproduced using the shared sample project workflow. Furthermore, the complete raw datasets and figure/graphic data tables (CSV/GeoPackage formats) will be provided by the corresponding author upon reasonable request. No personal or sensitive data are included.

Abbreviations:

AHP	Analytic Hierarchy Process
BN	Bayesian Networks
BWM	Best-Worst Method
CEC	Cation Exchange Capacity
FAO	Food and Agriculture Organization of the United Nations
GIS	Geographic Information Systems
LSP	Logic Scoring of Preference
MCDM	Multi-Criteria Decision Analysis
MCE	Multi-Criteria Decision-Making
MCDM	Multi-Criteria Evaluation
NDVI	Normalized Difference Vegetation Index
NH	Northern Hemisphere
OSB	Organized Industrial Zone
OWA	Ordered Weighted Averaging
RPM	Ratio Product Model
SLM	Sustainable Land Management
SLU	Sustainable Land Use
SOC	Soil Organic Carbon
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

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