



Investigating forest fire causes through an integrated Bayesian network and geographic information system approach

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Received: 3 January 2025 / Accepted: 12 April 2025 / Published online: 6 May 2025
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Abstract

Forests are among the most critical natural resources worldwide and are essential for a sustainable ecosystem. In recent years, climate change and human activities have increased their impact on forests, and forest fires-especially in summer- have caused significant forest losses globally. This paper integrates Bayesian Network (BN) and Geographic Information Systems (GIS) to pinpoint the possible causes of forest fires and analyze their complex interactions. The study used data from 1465 fires between 2017 and 2022 in Muğla province in southwestern Türkiye. Within the scope of the study, 11 variables were chosen, such as elevation, slope, aspect, wind speed, population density, and road network, to build a BN model that combines physical and human geographical features. These variables overlapped using the pairwise intersect tool from ArcGIS Pro during the BN model setup, and probability values were calculated. The overall probability of fire in the BN model was determined to be 0.81, with probabilities ranging from 0.81 to 0.56 in low-altitude, moderately sloped, and south-facing areas. Scenario analyses examined fire risk under different conditions, highlighting the most influential variables for fire prevention efforts. The study identified fire-prone areas as spatial data, revealing that densely forested coastal and certain inland regions are at higher risk, whereas bare high-altitude areas with steep slopes pose lower risk. The BN model can be further enhanced by incorporating additional variables, making it a valuable tool for future fire risk assessment and mitigation strategies research.

Keywords Bayesian networks (BN) · Geographic information systems (GIS) · Forest fires · Muğla

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1 Introduction

Forests are a vital natural resource that play a crucial role in maintaining environmental balance, biodiversity, and climate regulation. The state of forests in any region serves as a key indicator of ecological conditions (Jaiswal et al. 2002). They function as essential carbon sinks and contribute significantly to global CO₂ regulation (Trucchia et al. 2022; Gürsoy et al. 2023). However, the increasing frequency and intensity of forest fires, exacerbated by climate change, have led to widespread devastation, with mega-fires affecting vast areas during fire seasons (San-Miguel-Ayanz et al. 2021). The impact of these uncontrollable fires highlights the urgent need to understand fire dynamics and implement effective preventive measures (Salehi et al. 2023).

Forest fires are a natural phenomenon that occur when heat, oxygen, and combustible materials interact, affecting ecosystems by clearing forested areas and promoting vegetation regrowth and grazing opportunities (Trucchia et al. 2022; Gürsoy et al. 2023). However, wildfires threaten human life, property, and environmental stability, particularly in densely populated areas (Jolly et al. 2015). Since forest fires involve a multi-criteria and non-linear physical process, they are classified as one of the most complex emergencies (Trucchia et al. 2022). Accurately estimating fire probability is crucial for supporting forest protection and development plans, as well as mitigating the adverse effects of wildfires. Predicting forest fires with high accuracy and conducting effective fire prevention activities are necessary for sustainable development (Das et al. 2023). Therefore, creating fire susceptibility maps and analyzing the factors influencing forest fires is essential (Leuenberger et al. 2018).

Fire is not solely human-induced but is also influenced by factors related to proximity to roads and urban areas (Ganteaume et al. 2013; Leuenberger et al. 2018). Additionally, topography, climate, and vegetation significantly impact fire behavior (Mouillot et al. 2003). Models developed to analyze forest fires can be categorized into three types: (i) physically based models that utilize high-precision data, (ii) quasi-experimental models that rely on laboratory data, and (iii) empirical models that use statistical or machine learning techniques to identify parameters affecting wildfires (Hong et al. 2018). Empirical models aim to assess the impact of various parameters on fire occurrence and predict potential future fire locations using Geographic Information Systems (GIS) (Tien Bui et al. 2017; Hong et al. 2018; Das et al. 2023).

This study focuses on analyzing geographical factors that influence fire risk probability. The occurrence and spread of forest fires result from interactions among multiple factors (Dlamini 2010; Yang et al. 2021). Various studies have examined numerous geographical factors, including altitude, land use, slope, vegetation, tree species, road networks, and population density (Adab et al. 2013; Gheshlaghi 2019; Yılmaz and Öztürk 2019; Sevinc et al. 2020; Yang et al. 2021). Among these, elevation, slope, and aspect are considered critical factors influencing fire formation and spread (Eugenio et al. 2016; Sivrikaya and Küçük 2022). Additionally, climate variables such as temperature, precipitation, and wind speed significantly impact fire behavior, particularly in accelerating fire spread (Yılmaz and Öztürk 2019; Çetin et al. 2023). Due to the influence of human activities on fire occurrence, factors such as population density, proximity to road networks, and distance to urban centers are also considered crucial (Jaiswal et al. 2002; Parajuli et al. 2020).

The Bayesian Network (BN) approach is employed to model the relationships among these factors and assess their relative impact on fire events. BN is a powerful tool for understanding causal relationships between variables and visualizing the strength of

these relationships (Myers et al. 2004; Dlamini 2010). It enables updating probabilities to accommodate new scenarios or adapt to evolving conditions (Ballari et al. 2012). BN models' flexibility and computational feasibility have encouraged researchers to explore their application in various domains (Marcot and Penman 2019). Enhancements in BN models include classification, incorporation of hidden variables, confidence assessment, and GIS integration. These advancements support decision-making systems and analyze system dynamics (Marcot and Penman 2019). GIS is a valuable tool for mapping spatial data such as elevation, slope, wind speed, aspect, road networks, and population density, and it is widely used in risk assessments, location analyses, and optimizing accessibility routes (Konurhan et al. 2023). Integrating GIS with BN allows spatial data to be analyzed probabilistically within a causal framework (Sevinc et al. 2020; Zhang et al. 2022; Lu et al. 2024). This integration allows spatial data obtained from GIS to be modeled in BN to predict fire probabilities, providing deeper insights into the influence of spatial and probabilistic fire risk factors. Due to these advantages, BN-GIS integration has been applied in various studies (Grêt-Regamey and Straub 2006; Sevinc et al. 2020; Zhang et al. 2022; Lu et al. 2024).

A review of the GIS literature reveals numerous studies that have identified fire-prone areas using multi-criteria decision-making (MCDM) methods combined with GIS (Jaiswal et al. 2002; Dlamini 2010; Gheshlaghi 2019; Nuthammachot and Stratoulis 2021; Coşkun and Toprak 2023). Similarly, BN has been widely applied across various research fields (Wang and Vassileva 2003; Arroyo-Figueroa and Sucar 2013; Marcot and Penman 2019). For instance, Mihunov and Lam (2020) explored drought resilience dynamics in 503 counties across the South-Central USA, while Sun et al. (2006) introduced a BN-based model for traffic flow forecasting by analyzing road network interactions. Although relatively limited, some studies have integrated BN and GIS to identify fire-prone areas (Dlamini 2010; Noroozi et al. 2024). Dlamini (2010) examined the spatial and environmental factors influencing forest fires in Swaziland using a BN model, demonstrating high model accuracy in evaluating variables such as land use, elevation, and climate. Sevinc et al. (2020) applied BN to predict potential causes of wildfires and their interactions, identifying critical factors such as temperature, wind speed, burnt area extent, and proximity to settlements. Yılmaz and Öztürk (2019) proposed a dynamic approach integrating BN and GIS for forest fire hazard analysis, emphasizing the importance of updating hazard maps with temporal and spatial data.

In recent years, major wildfires in the Muğla region, including the catastrophic fire that began on July 29, 2021, and lasted for 15 days, have underscored the importance of fire risk assessment for protecting both natural and human assets (Atmaca et al. 2022). Using BN and GIS integration, this study collected and mapped spatial data such as elevation, aspect, population density, temperature, and wind speed. These spatial variables were overlaid in GIS based on the BN network structure, and their contributions to fire probability were assessed. A spatial risk map was also developed using study outputs. Unlike conventional fire risk analyses that rely on limited criteria, this research comprehensively evaluates fire risk probabilities under varying conditions using large-scale spatial analysis and scenario modeling. GIS-BN creates a dynamic decision-support framework applicable to large-scale risk management. This study offers valuable recommendations for policymakers, regional planners, and crisis management experts, contributing to proactive wildfire risk mitigation strategies and laying a foundation for future research.

The remainder of this paper is structured as follows: Sect. 2 describes the study area. Section 3 outlines the proposed method, including the data collection, data analysis, BN-GIS integration and sensitivity analysis processes. Section 4 and Sect. 5 present the results

and discussion to existing studies, respectively. Finally, Sect. 6 concludes the paper by summarizing the key contributions, highlighting limitations, and suggesting directions for future research.

2 Study area

Muğla Province is located at approximately $37^{\circ}21'54''$ N latitude and $28^{\circ}36'36''$ E longitude, covering a total area of around 12,974 km². As illustrated in Fig. 1, the province lies in the southwestern part of the Anatolian region of Türkiye. It includes the southern section of the Menteşe region and the western part of the Teke region. Muğla is bordered by the Aegean Sea to the west and the Mediterranean Sea to the south.

The province is home to several mountainous regions, including Gökbel Mountain (1422 m), Oyuklu Mountain in the north, Sandıras Mountain (2295 m) in the northeast, Gök Tepe (2407 m) in the east, and Dumanlı Mountain (1973 m) and Akdağ (3024 m) in the southeast. The region where Muğla province is located draws attention with its highly defective topography. There are slightly wavy and flat sections in many places with a surface split by rivers. The fact that the ridges and hills are close to each other shows that this region is shaped entirely on an erosion surface. The region's mountains rise on this erosion surface, and depressions are located on this surface (İkiel 2004). To the west of the region, between the Gulf of Güllük and the Gulf of Gökova, lies the Bodrum peninsula with a broad head and narrow neck. The area with medium-height hills rises towards the east. In the south of Muğla are two peninsulas, one orientated to the west and the other to the southwest, and a wide isthmus connecting them. The peninsula extending to the west is



Fig. 1 Location map of Muğla province

Datça or Reşadiye peninsula, and the one extending to the southwest is the Bozburun peninsula (Daraçya peninsula). Marmaris Bay is located south of the isthmus section where these two peninsulas meet. It is separated from the Datça peninsula by Hisarönü Gulf in the north, and the head part of the peninsula is divided into two parts by Sömbeki Gulf in the west. (Darkot and Tuncel 1978). The coasts of Southwestern Anatolia are highly fragmented and indented, and although there are shapes resembling a ria, estuary, and harbor, none of these shapes are dominant on their own (Erol 1991). Muğla is a coastal region surrounded by the Aegean Sea to the west and the Mediterranean Sea to the south, and the Mediterranean climate is observed in this region. In Muğla and its surroundings, there is a transition between the thermal regime of the Mediterranean and the continental climate, which causes cool-temperate winters and hot summers. Factors such as altitude and distance to the sea create significant differences between coastal and inland depressions, and these differences become more pronounced, especially in winter. In the study region, where the Mediterranean precipitation regime is effective, 55–61% of the annual precipitation occurs in winter and 1–5% in summer. Due to the climatic conditions, the study area is located in the Mediterranean (Aegean—Mediterranean) phytogeographical region. In areas where the natural vegetation is intact, red pine forests are found up to 800–1000 m, and larch forests are found in higher areas. The maquis, typical Mediterranean climate plants, become widespread in these areas (Atalay 1994).

In the study area, which has an essential position in forest presence, forest fires have occurred almost every period from the records to the present day. In this context, since 1977, the number of fires recorded as of the end of 2023 is 13,119, and the average per year is 279 fires/year. In this period, the minimum number of forest fires was 133 in 1983, and the maximum was 415 in 2007. In the same period, 141,342.9 ha of the forest area was burnt, and the average amount of the area burnt was 3,007.30 ha/year. In this period, at least 155.8 ha in 2010 and 52,219.5 ha in 2021, forest area was damaged by forest fires (2023 Forest Fires Assessment Report 2023).

3 Method

In this section, we outline the methodology employed in our research, as illustrated in Fig. 2. The first stage involved data collection and analysis, including acquiring geospatial data in a GIS environment and normalizing datasets. To enhance the overall accuracy of the network, the number of states or the discretization of continuous variables was limited to three classes: low, medium, and high (Kalácska et al. 2005; Marcot et al. 2006). This classification also facilitated parameterization (Pollino et al. 2007). In Bayesian Networks with multiple explanatory variables, constraints are necessary to maintain manageability, as conditional probability tables (CPTs) can become exceedingly large (Dlamini 2010; Spiegelhalter et al. 1993). Therefore, both Dirichlet and Beta distributions were used in the study to model probabilities. The Dirichlet distribution was employed for modeling multivariate probabilities, whereas binary variables (e.g., presence/absence or yes/no) were simplified using the Beta distribution. This approach streamlined the calculation of CPTs, improving the network's efficiency. Aspect and land use criteria, as presented in Table 2, were expressed in discrete categories rather than the three-tier classification due to their inherent nature. All parameters directly or indirectly impacting forest fire occurrence were integrated into the GeNIe software. The pairwise intersection process was applied in GIS for data layers corresponding to the criteria whose classes had been determined. Pairwise

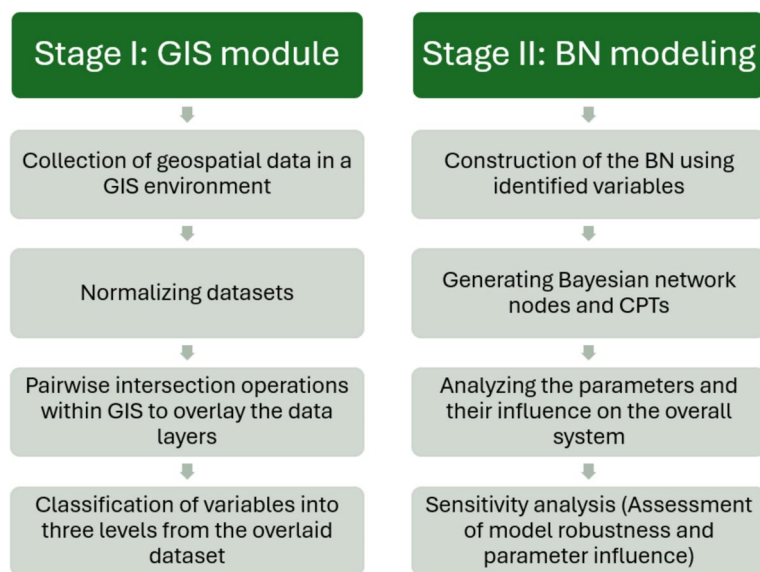


Fig. 2 The flowchart of the GIS-BN integration for the forest fire risk

intersection involves identifying the common areas of different spatial data layers within a GIS environment, thereby integrating data from multiple explanatory variables into a unified dataset for each location (<https://pro.arcgis.com/en/pro-app/latest/tool-reference/analysis/pairwise-intersect.htm>). This method ensured that all variables included in the BN modeling shared the same spatial unit. Consequently, network nodes were generated, and CPTs were developed to represent relationships between variables. Additionally, model parameters were analyzed to evaluate the influence of each variable on the overall system. The final stage involved conducting a sensitivity analysis to assess the robustness of the model. This analysis systematically evaluated the impact of different parameters, providing insights into their relative significance and ensuring the reliability of the model results.

The study was conducted at the scale of Muğla province, with all analyses performed within its provincial boundaries. The BN model utilized raster data, where each pixel was considered an independent data point. Consequently, analyses were carried out across the entire province. Furthermore, the fire risk map allowed for evaluating risk levels at the district level. Given that fire management strategies require tailored approaches at both local and regional scales, the study's findings offer valuable insights for provincial decision-makers and local administrators. Accordingly, large-scale fire risk management plans can be formulated at the provincial level, while more targeted measures can be implemented at the district scale.

3.1 Data collection

The dataset used in this study consists of fire records maintained by the General Directorate of Forestry (GDoF) in the Muğla region from 2004 to 2022. To ensure data relevance and manageability, 1,463 fire records from 2017 to 2022 were considered. Since the dataset does not specify the causes of these fires, they are broadly categorized as

forest fires, encompassing occurrences in forested, agricultural, urban, and bare areas within the Muğla province.

Eleven key variables were identified based on the study area's physical and human geographical characteristics and insights from relevant literature. These variables include altitude, slope, aspect, average temperature, average rainfall, distance to main roads, and distance to settlements. The classification of these variables follows the spatial analysis methodology: “Continuous” variables (e.g., elevation, slope, temperature) exhibit a range of values, while “Discrete” variables (e.g., aspect, land use) are distinctly categorized. This classification facilitates effective integration with the BN model (Table 2).

These variables served as the primary input data for constructing the BN model. The selection of key variables influencing forest fire occurrence was guided by the natural and human characteristics of the study area, along with findings from previous research on forest fire risk (Jaiswal et al. 2002; Brooks and Matchett 2006; Falk et al. 2007; Dlamini 2010; Zwirgmaier et al. 2013; Sevinc et al. 2020; Coşkun and Toprak 2023; Almeida et al. 2024). Variable selection in a BN model depends on the study's objectives, requiring a careful balance between computational load, model complexity, parameterization, and accuracy (Dlamini 2010).

Variables such as the time elapsed since the last fire, the season of the previous fire, and the total burned area were initially considered; however, incomplete or low-resolution data at the regional level prevented their integration into the model. While global satellite datasets could have served as an alternative data source, their resolution and accuracy were deemed insufficient for this study, leading to their exclusion.

Furthermore, previous BN-based fire modeling studies suggest that 10 to 12 variables are generally sufficient for accurate predictions (Dlamini 2010; Sevinc et al. 2020). Including more variables beyond this range significantly increases computational load and leads to excessive growth in CPTs (Spiegelhalter et al. 1993). Therefore, 11 variables were selected. Additionally, the appropriate threshold values for these variables were determined using the Quantile and Natural Breaks (Jenks) classification algorithms in ArcGIS software, with special attention given to the distribution of relevant variables when defining these thresholds (Table 1).

Table 1 Classification ranges of variables used in the fire risk model

Criteria	Class 1	Class 2	Class 3
Elevation	> 480 m	481–1200 m	< 1201 m
Slope	> 11°	12–24°	< 24°
Wind speed	> 4	4.1–5.1	< 5.2
Population density	> 100,000	100,000–463,500	< 463,500
Average temperature	> 4.1 °C	4.1–15 °C	< 15 °C
Average precipitation	> 1.076 mm	1.076–1.440 mm	< 1.440 mm
Distance to main roads	> 1000 m	1000–3000 m	< 3000 m
Distance to electricity lines	> 5000 m	5000–10,000 m	< 10,000 m
Distance to settlements	> 3000 m	5000–15,000 m	< 15,000 m

3.2 Data analysis

The variables used in the study were determined as mean annual precipitation, mean annual temperature, and wind speed under the climate main heading, elevation, slope, aspect, and land use under the topography main heading, population density and distance to settlements under the human geography heading and distance to power lines and distance to main roads under the location heading (Fig. 3). A brief description of the explanatory variables is given in Table 2. All raster data layers used in the study have a spatial resolution of 30 m. This resolution is sufficient for observing regional differences and performing detailed fire risk analyses in Muğla province. Moreover, it also provides the opportunity to produce meaningful and interpretable results by maintaining computational efficiency in data processing. A 30 m resolution is preferred as a common standard in many studies conducted in forest fire risk modeling (Dlamini 2010). Therefore, 30 m resolution, which offers a balanced approach between model accuracy and processing load, was used in the analyses.

Climate determines the vegetation in a region and thus plays a dominant role in creating fire-prone areas. The drier the climate in each area, the more fire-prone the area will be (Jaiswal et al. 2002). Likewise, seasonal rainfall and wind speeds are the most critical climatic elements that affect the occurrence or persistence of fire. The study area has significant forest covers and scorching and dry weather, especially in the summer months (June, July, and August), with almost no rainfall. Therefore, regarding climate, the study area may be vulnerable to forest fires during these periods. Topography is a crucial physiographic factor related to wind behavior and thus influences the fire susceptibility of the

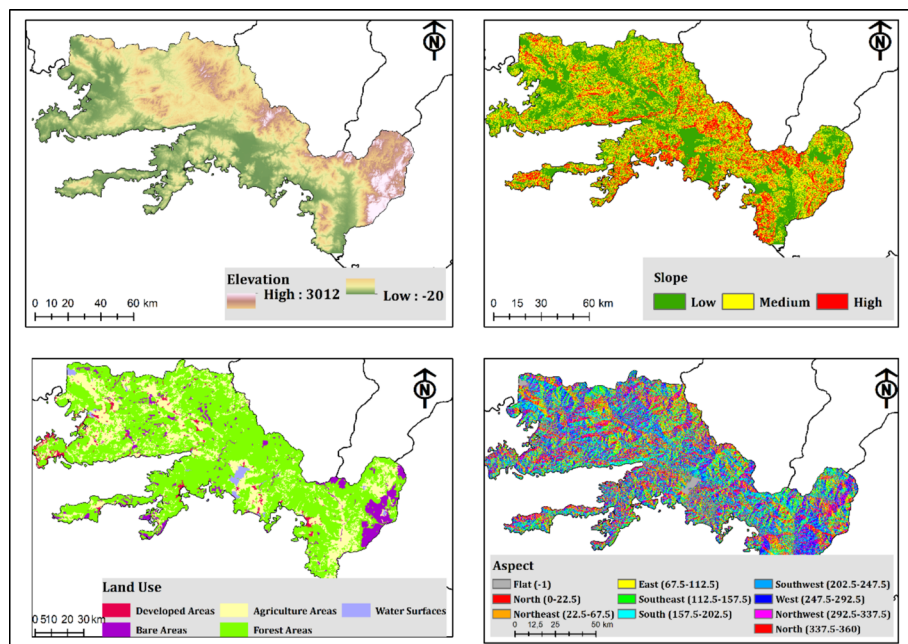


Fig. 3 Topography variables used in the study

Table 2 Data sources and description of the independent variables

Variable	Type	Scale	Situation	Source
Elevation	Continuous	High, Medium, Low	United States Geological Survey-Digital Elevation Model (DEM) (30 m resolution)	United States Geological Survey
Slope	Continuous	High, Medium, Low	United States Geological Survey- DEM (30 m resolution)	United States Geological Survey
Aspect	Discrete	Flat, North, East, West, South	United States Geological Survey- DEM (30 m resolution)	United States Geological Survey
Land use	Discrete	Developed areas, Transportation, Mine, Agriculture, Vineyard gardens, Olive groves, Plant Exchange, Forest, arid vegetation, Coastal, Bare, Marshland, Water, Sea-Ocean	Coordination of information on the environment (Based on land use class)	Coordination of information on the environment
Wind speed	Continuous	High, Medium, Low	Global Wind Atlas (10 height)	Global Wind Atlas
Population density	Continuous	High, Medium, Low	Kernel analysis (30 m resolution)	Turkish Statistical Institute
Average temperature	Continuous	High, Medium, Low	Inverse distance weighting (IDW) analysis (30 m resolution)	Turkish State Meteorological Service
Average precipitation	Continuous	High, Medium, Low	Inverse distance weighting (IDW) analysis (30 m resolution)	Turkish State Meteorological Service
Distance to main roads	Continuous	High, Medium, Low	Lines (Buffer analysis)	OpenStreetMap
Distance to electricity lines	Continuous	High, Medium, Low	Lines (Buffer analysis)	OpenStreetMap
Distance to settlements	Continuous	High, Medium, Low	Lines (Buffer analysis)	OpenStreetMap

region. Fire travels most rapidly up slopes and least rapidly down slopes. Therefore, elevation and slope values in an area are important because they affect both the increase of fire and the response to fire (Jaiswal et al. 2002; Yang et al. 2021). In the study area, elevation and slope values vary wildly. Large forest areas are concentrated in areas with steep and high slope values. The elevation values in the study area exceed 3000 m in certain regions. In addition, the aspect also plays an influential role in the spread of fire. Human interaction and location characteristics are also effective in forest fires. Indeed, the main factors often used to characterize the impact of human activities and location on wildfires are population density, distance to settlements, road density, distance to roads, and distance to power lines. Population density, settlement density, and road density increase human interaction with forests, while power lines crossing forest areas can start a forest fire by sparking during a fault (Yang et al. 2021). From this point, relevant variables are included in the study.

3.3 BN and GIS integration

BNs naturally represent systems and are frequently employed to model environmental processes, creating a strong synergy with GIS (Ames and Anselmo 2008; Sevinc et al. 2020; Zhang et al. 2022; Lu et al. 2024). In this article, BN and GIS were integrated to conduct spatial and causal analyses of factors influencing forest fire occurrence. BNs allow the incorporation of spatial data into a model, enabling more precise analysis of fire scenarios. Initially, data on spatial variables affecting forest fires were collected and analyzed using GIS software. These variables included topographic features (e.g., slope, elevation), land use, vegetation, meteorological data (e.g., temperature, precipitation), and human activities (e.g., population density, road network). ArcGIS Pro software was employed, applying histogram examinations and quarter-value discretization functions to convert continuous variables into discrete categories. To enhance model accuracy and manageability, variables were limited to a maximum of three states: low, medium, and high. This classification was informed by field knowledge and local expert opinions, ensuring appropriate state values for each variable. The class limitation also significantly reduced processing time. Approximately 8,000 overlapping operations were analyzed using these discrete classes.

The state of each criterion (as indicated *low*, *medium*, and *high*) corresponded to specific spatial areas within the GIS. These areas overlapped with regions represented by nodes in the BN model, creating the final mapped areas. The BN model overlaid and analyzed variables associated with fire occurrence (e.g., average temperature, slope). If a spatial area coincided with all critical factors contributing to fire risk and a fire was recorded in that location, it was assigned a value of 1 (fire—yes). Conversely, areas without fire occurrence were assigned a value of 0 (no fire). Historical data on fires in Muğla province from 2017 to 2022 were mapped to determine fire locations, and overlapping occurrences were evaluated.

The BN model was developed based on literature reviews and expert judgments. Using GeNIe software, causal relationships between variables were graphically represented with directed arrows. The model was designed with a simple, shallow topology to prevent overfitting while maintaining an acceptable prediction error rate. Variables were discretized into three states (low, medium, and high) using ArcGIS Pro, and CPTs were created based on GIS data, field information, and calculated probability relationships.

The GIS-derived data were integrated into the BN model using GeNIe software. This BN-GIS integration facilitated the analysis of variable influences on forest fires, their probabilities of causing fire, and their spatial impacts. The results provided valuable information

on fire risk assessment and informed the development of strategic fire prevention measures. The graphical structure of the BN-GIS model effectively visualized node relationships and results, streamlining the analysis process and optimizing its outcomes.

An essential stage of the BN-GIS integration is creating a spatial risk map based on the data obtained. A fire risk map was created for the study area with the data received from the CPT tables created due to overlapping with the ArcGIS tool. This risk map presents the risky areas of fire in the study area.

3.4 Sensitivity analysis

Sensitivity analysis is a type of analysis performed to understand the effects of changes in the inputs of a system or model on its outputs (Demirel et al. 2024). This study helps determine which variables are more sensitive/important by determining the effects of the variables on fire risk. This analysis helps to visually and numerically determine the variables that affect the fire risk the most and the probability values of these variables. Knowing the variables affecting fire can pave the way for fire risk predictions. The sensitivity analyses determined within this framework determined the probability of fire and the status of each variable within the fire risk.

4 Results

The proposed BN model provides a robust framework for integrating environmental and spatial variables affecting wildfires. The model is an essential tool for estimating fire occurrence probabilities by assessing the impact of various factors on fire risk. In the model, separate networks were developed that represent the initial states of fire-related variables through probability distributions for each node. These probabilities indicate the likelihood of each variable being in a given state and provide essential assessments of the key determinants of fire activity. To further develop the model, a sensitivity analysis was also performed to assess the impact of each variable on the outcomes of the fire occurrence node. A risk map was also created using the data from the BN model.

4.1 Analysis of variables affecting fire risk and probability-based interpretation

This section analyzes the effects of spatial and environmental variables affecting forest fires on fire probability scenarios. When the state of each variable is determined, changes in fire risk are analyzed in line with the probability values produced by the model. Scenario analyses are important in determining the areas that should be prioritized in fire management strategies. Evaluating the probability-based effects of variables has the potential to increase the accuracy of fire risk estimates and contribute to the decision-making processes of the model.

Land use is a crucial variable that directly influences fire probability. According to the results for forested areas, the probability of fire is 93%, while the probability of no fire is 7% (Table 3). This finding highlights that forested areas significantly increase fire risk and have a relatively high fire potential. Forested areas are particularly susceptible to fire due to their dense vegetation and abundance of flammable natural materials, making them prone to ignition and rapid fire spread. The data confirms that the model effectively identifies forested areas as a strong determinant in fire prediction. The exceptionally high probability

Table 3 Effect of variables on the fire

Scenario	Node	State	Fire probability
1	Land use	Developed areas	0.59
2	Land use	Forest	0.93
3	Aspect	Flat	0.25
4	Aspect	South	0.86
5	Population density	High	0.84
6	Population density	Low	0.76

of fire in these areas underscores their vulnerability, while reducing uncertainty within the model.

When “urban areas” were set to 100% within the land use variable, the probability of fire was calculated as 59%, while the probability of no fire was 41% (Table 3). Although the fire risk in urban areas is lower than in forested regions, a 59% probability of fire suggests that human activity and the materials used in urban structures contribute to increased fire risk. This risk is particularly evident in densely populated urban centers such as Bodrum, Marmaris, and Fethiye, where high tourism activity increases the likelihood of fire incidents. The fire probability of 59% indicates that urban areas are not entirely fire-resistant and still face a significant fire hazard. Factors such as electrical infrastructure, vehicles, buildings, and other artificial structures further contribute to fire outbreaks in urban environments.

When the “land’s aspect” was set to 100% south, the probability of fire was calculated as 86%, while the probability of no fire was 14%. Southern slopes have a high fire probability because they receive more sunlight, leading to drier and hotter conditions. These conditions cause vegetation to dry out, making it more susceptible to fire. The fire probability on south-facing slopes can reach as high as 89%, highlighting their significant contribution to fire risk. In contrast, when the land’s aspect was set to 100% flat, the probability of fire was determined to be 25%, while the probability of no fire was 75%. This stark difference underscores the role of land aspect in fire risk. While southern slopes exhibit a very high fire probability of 89%, flat areas show a much lower fire probability of 25%, making them relatively safer and low risk (Table 3).

When population density was set to 100% high, the probability of fire was calculated as 84%, while the probability of no fire was 16%. High population density is also a critical factor that increases fire risk, as rapid human activity in these areas can directly contribute to fire outbreaks. In densely populated regions, fires are more likely due to careless behavior or infrastructure-related issues. Conversely, when population density was set to 100% low, the probability of fire decreased to 76%, while the probability of no fire increased to 24%. Although fire risk remains significant even in areas with low population density, the probability of fire is slightly lower due to reduced human influence. This comparison highlights that human activity plays a key role in fire risk, with higher population density leading to a greater likelihood of fire incidents (Table 3).

Scenarios in which the effect of more than one variable is analyzed simultaneously are also examined, and simultaneously, the impact of a single variable is also discussed. Instead of analyzing the effect of a single variable on fire risk, it may be important to understand how the probability of fire changes when multiple variables coexist. The effect of multiple variables is essential in predicting the probability of fire more precisely and revealing how the interaction of these variables is reflected in fire risk. Accordingly, when

land use is set as 100% forest, population density as 100% low, aspect as 100% south, slope as 100% moderate, and elevation as 100% moderate, the probability of fire is extremely high at 94% (Fig. 4). This shows how interrelated environmental factors increase fire risk. Although each variable alone affects the probability of fire, as seen in this scenario, fire risk reaches much more severe when multiple factors come together. Forested areas are areas with natural fire risk and are one of the most important factors that increase the probability of fire due to dense vegetation and excessive combustible materials. Adding a variable such as the southern direction, which is exposed to more sunlight and heat, causes the vegetation to dry out and become flammable. Therefore, the south orientation of forested areas increases the likelihood of fire outbreaks. The 100 percent southerly aspect is an important environmental factor that increases the fire risk, as hot and dry conditions can predispose to fire. The scenario also includes moderate slopes and areas of moderate elevation. Medium-sloping terrain allows for rapid fire spread because fire can move quickly uphill or downhill. The elevation factor is another variable that affects fire spread. Moderate elevation affects air circulation, allowing the fire to feed on oxygen and causing lower humidity levels, making it more difficult to control the fire. Although low population density slightly reduces the reduction of fire, the effect of this variable is limited under such intense influence of environmental factors. While the human factor does not significantly impact this, natural factors significantly increase the probability of fire. As a result, the fire risk in these multiple scenarios is calculated with a high probability of 94%, indicating that environmental factors, when combined, can dramatically increase the probability of fire. Mutually reinforcing variables such as forested area, southerly aspect, moderate slope, and moderate elevation increase the fire risk even further. This multivariate analysis emphasizes that fire predictions should not be based solely on a single factor but rather on the interactions of all relevant variables.

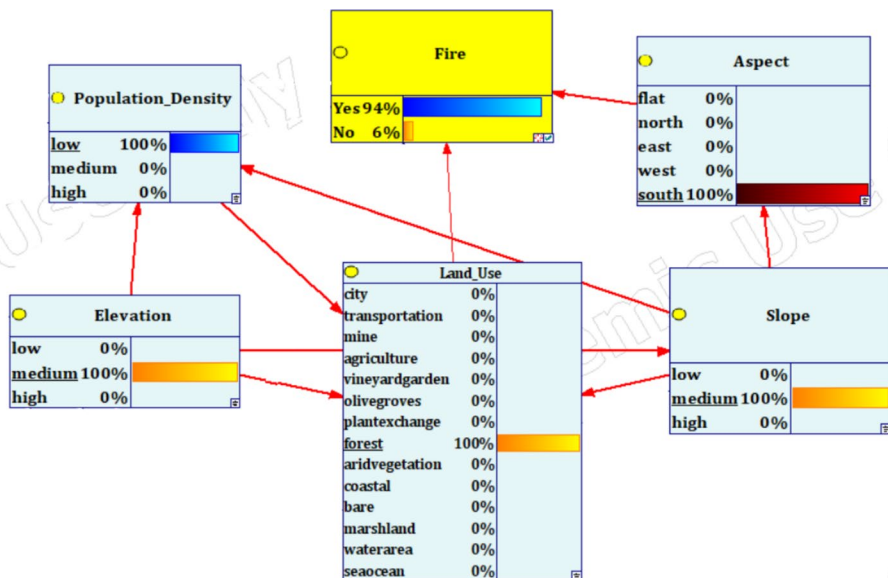


Fig. 4 Effect of multiple variables on fire probability

4.2 Analysis of strong influences of factors affecting fire risk

Figure 5 and Table 4 show the strength and direction of the interactions between the variables in the BN model. In Fig. 5, the relationships between variables are visually represented by arrows, and the thickness of the arrows symbolizes the strength of these relationships. For example, there is a strong relationship between elevation, average rainfall, average temperature, and fire risk (demonstrated as “Fire” in the Fig. 5). The thickness of the arrows between these variables indicates that their influence on Fire is also high. Likewise, the Aspect variable has a substantial direct effect on Fire. This shows the contribution of land aspect and topography to fire risk. The land use variable also has a high impact strength with other variables. The effect of land use on the main criterion of Fire is also strong, and its impact on fire is significant. The power of influence between variables such as population density, road network, and settlement units is already substantial.

Table 4 shows the interactions between variables in more detail. Accordingly, it evaluates the interactions between the variables in the model in terms of average, maximum, and weighted effects. These values quantitatively reveal the effect between variables. High mean and maximum values indicate that the effect of the relevant variable on the other variable is more substantial. In this context, among the variables that directly affect fire risk is the Aspect variable, which has a low mean value, but the maximum value of 1 is calculated with the Fire link. This shows that the aspect variable is important in terms of fire occurrence. It is interpreted that south-facing slopes may be more susceptible to fire risk because they receive more sunlight. Likewise, the maximum effect of the link between average precipitation and Fire is calculated as 1, indicating that average precipitation is

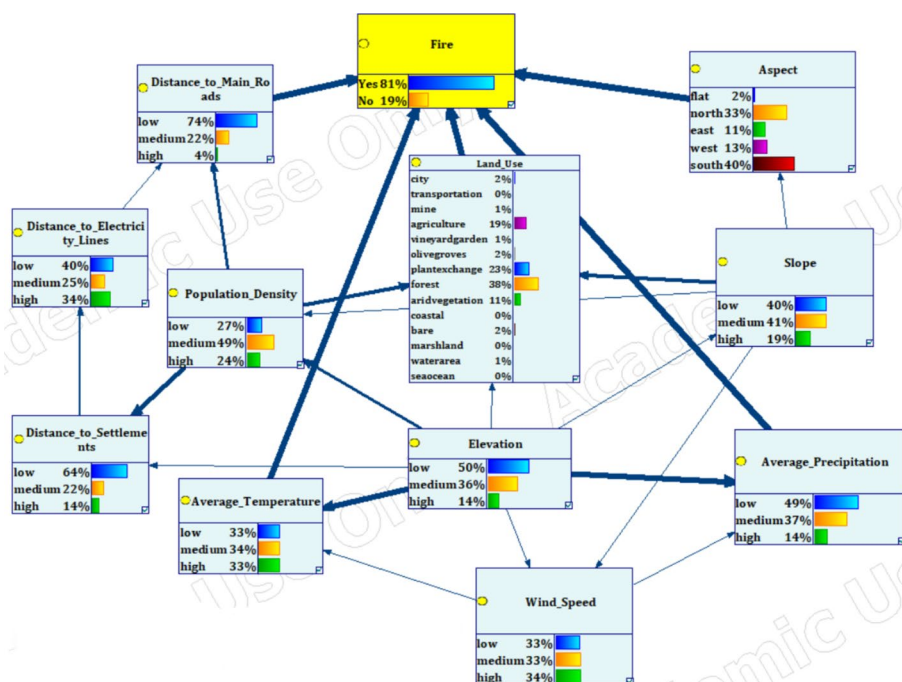


Fig. 5 Strength of influence representation

Table 4 Detailed demonstration of strength of influence

Parent node	Child node	Average*	Maximum [†]	Weighted [‡]
Aspect	Fire	0.06	1.00	0.06
Average precipitation	Fire	0.13	1.00	1.00
Average temperature	Fire	0.12	1.00	0.12
Distance to electricity lines	Distance to main roads	0.05	0.19	0.05
Distance to main roads	Fire	0.08	1.00	0.08
Distance to main roads	Distance to electricity lines	0.20	0.31	0.20
Distance to electricity lines	Slope	0.10	1.00	0.10
Elevation	Wind speed	0.13	0.23	0.13
Elevation	Average precipitation	0.87	0.94	0.87
Elevation	Average temperature	0.64	0.87	0.64
Elevation	Population density	0.35	0.47	0.35
Elevation	Land use	0.16	0.26	0.16
Elevation	Distance to settlements	0.10	0.24	0.10
Elevation	Fire	0.14	1.00	0.14
Elevation	Land use	2.00	0.56	1.00
Land use	Fire	1.00	1.00	1.00
Population density	Land use	0.52	0.79	0.52
Population density	Distance to settlements	0.22	0.43	0.22
Population density	Distance to main roads	0.02	0.04	0.02
Population density	Aspect	0.07	1.00	0.07
Slope	Wind speed	0.11	0.25	0.11
Slope	Population density	0.21	0.26	0.21
Slope	Land use	0.05	0.11	0.05
Slope	Average precipitation	0.01	0.05	0.01

*Thickness of arcs can be based on one of the three: *Average* (default in GeNIe), *Maximum*, and *Weighted*. *Average* takes the plain average over distances

[†]*Maximum* uses the largest distance between distributions

[‡]*Weighted* weighs the distances by the marginal probability of the parent node

important in determining fire risk and that low precipitation amounts significantly affect fire occurrence. The maximum value of the link between Average Temperature and Fire is calculated as 1, indicating that the temperature variable is among the factors that directly affect fire risk. The maximum value of the link between the Land Use variable and Fire is calculated as 1. This shows that land use has a strong direct impact on fire risk. Depending on the land use, forested areas, agricultural lands, or residential areas can have significantly different impacts on fire risk. The effect of elevation on some variables in the model is also quite significant. In particular, the maximum link between the elevation variable and average precipitation is calculated as 0.94, indicating that elevation is one of the strongest variables directly affecting the amount of rainfall. This is a confirmation of the fact that higher altitude areas receive more precipitation, which can have a direct impact on fire risk. The maximum value of the average temperature link of the elevation variable is calculated as 0.87, which shows that the effect of elevation on temperature is quite strong. Another strong link in the model is between population density and land use, with a maximum value of 0.7996. This result shows that population density is an important variable

shaping land use and that human activities may have indirect effects on the occurrence of forest fires. Similarly, the maximum value of the link between the elevation variable and population density is 0.47, indicating that the elevation variable significantly affects population density. Variables with lower maximum values include the link between slope and wind speed (0.25) and the link between slope and population density (0.22). This indicates that the slope factor has a particular influence on wind speed or population density, but this influence is lower than other variables. In addition, proximity to power lines and distance to settlements indirectly affect fire risk. Although proximity to power lines is not among the variables with the strongest direct link to fire, it is associated with distance to main roads (0.31) and slope (1.00), indicating that power lines can cause spark-induced fires, especially with wind. Distance to settlements shows a strong relationship with elevation (0.24) and population density (0.43), indicating the contribution of human influence to fire risk and the importance of fire response time.

4.3 Sensitivity analysis

According to the output results, the “aspect” variable significantly affects fire probability. Consequently, forest fire risk is higher on flat and southern slopes than high, steep, and northern slopes. This shows the effect of topographic conditions on fire risk. For example, fire probability increases to 0.81 for flat and medium slope combinations of aspect and slope. Therefore, it shows how fire risk increases depending on the physical and geographical characteristics of the land and carries serious risks, especially in flat areas (Table 5).

Meteorological variables also seriously affect the probability of fire. Variables such as average temperature and wind speed play a vital role in the occurrence of fires. The combination of temperature, wind speed, and low altitude are among the factors that significantly increase the probability of fire. Especially low temperatures and low wind speeds

Table 5 Sensitivity analysis results for the *Yes* fire occurrence scenario

Sensitivity for fire = yes/current value: 0.81/reachable range: [0.56–0.82]

No	Case	Target value range	Current parameter value
1	Aspect = Flat/Slope = Medium	0.81–0.56	0.0024
2	Aspect = Flat/Slope = Low	0.82–0.61	0.37
3	Average Temperature = Low/Elevation = Low/Wind Speed = Low	0.81–0.67	0.0077
4	Average Temperature = Low/Elevation = Low/Wind Speed = Medium	0.81–0.69	0.01
5	Aspect = Flat/Slope = High	0.81–0.69	0.09
6	Average Precipitation = Medium/Elevation = Low/ Wind Speed = Low	0.82–0.71	0.09
7	Average Precipitation = Low/Elevation = Low/Wind Speed = Low	0.71–0.82	0.90
8	Average Temperature = High/Elevation = Medium/Wind Speed = High	0.81–0.70	0.003
9	Average Temperature = High/Elevation = Medium/ Wind Speed = Medium	0.81–0.71	0.001
10	Average Temperature = Low/Elevation = Low/Wind Speed = High	0.81–0.71	0.01

are observed to increase the probability of fire. This finding reveals that fire risk in the study area may be high in hot and dry weather and regions and low temperatures and wind speeds. Wind speed is an essential factor affecting the rate of fire spread. While high wind speeds can accelerate the spread of fire, low wind speeds can cause the risk to be higher in the area where the fire starts (Table 5).

Average Precipitation is another crucial factor affecting fire risk. In areas with low precipitation levels, fire risk increases. However, this analysis has shown that moderate Precipitation, combined with low temperature and wind speed, can further increase the probability of fire. This finding suggests that fire risk can be high in arid and certain humid conditions. For example, in areas with moderate rainfall and low wind speed, the probability of fire can be as high as 0.82. The impact of rainfall plays a complex role in estimating fire risk. Therefore, accurately analyzing the impact of rainfall is considered a critical element in fire risk management. In addition to topographic and meteorological variables, Elevation significantly influences fire probability. Low altitudes and combinations of temperatures and wind speeds increase the fire risk. According to the analysis, fire risk is higher in low-altitude areas than in high-altitude areas, confirming that topographic factors play a critical role in determining fire risk (Table 5).

The sensitivity analysis, where the fire situation is considered “No”, examines the probabilities of fire not occurring in scenarios where various environmental and topographic variables are considered together. The analysis shows how different combinations of variables affect fire risk, focusing on factors that reduce the probability of fire occurrence (Table 6).

The combination of flat areas (Aspect=Flat) and moderate slope (Slope=Medium) stands out as one of the situations with the highest probability of fire not occurring. In this case, the probability of fire is assessed in a range of up to 0.17–0.43, indicating that the terrain significantly reduces the fire risk. While the fire risk increases on sloping terrain, this risk is balanced by keeping the slope at moderate levels. Besides, it is important to note

Table 6 Sensitivity analysis results for the No fire occurrence scenario

Sensitivity for fire = no/current value: 0.18/reachable range: [0.17–0.43]

No	Case	Target value range	Current parameter value
1	Aspect = Flat/Slope = Medium	0.18–0.43	0.0024
2	Aspect = Flat/Slope = Low	0.17–0.38	0.03
3	Average Temperature = Low/Elevation = Low/Wind Speed = Low	0.18–0.32	0.0077
4	Average Temperature = Low/Elevation = Low/Wind Speed = Medium	0.18–0.30	0.01
5	Aspect = Flat/Slope = High	0.18–0.30	0.0015
6	Average Precipitation = Medium/Elevation = Low/ Wind Speed = Low	0.17–0.28	0.09
7	Average Precipitation = Low/Elevation = Low/Wind Speed = Low	0.28–0.17	0.90
8	Average Temperature = High/Elevation = Medium/Wind Speed = High	0.18–0.29	0.0037
9	Average Temperature = High/Elevation = Medium/ Wind Speed = Medium	0.18–0.28	0.0013
10	Average Temperature = Low/Elevation = Low/Wind Speed = High	0.18–0.28	0.01

that Aspect=Flat (flat terrain) is observed in both fire probability *Yes* and fire probability *No* cases. In the case of no fire (*No*), flat terrain (Aspect=Flat) generally reduces the fire risk. This may mean that the terrain structure makes it more difficult for fires to spread. In particular, the absence of natural obstacles (e.g., slopes that change the direction of the wind) necessary for fire spread in flat terrain may increase the probability of a fire not starting.

In the case of a *No* fire, low temperatures stand out as an important factor that increases the probability that the fire will not occur. Low-temperature levels do not provide the conditions necessary for a fire to start; therefore, the fire risk remains low. As it is difficult for a fire to start at low temperatures, low temperatures can also make it difficult for a fire to spread. Thus, when the temperature decreases, the probability of fire decreases to 0.17–0.28. The combination of low wind speed and low temperature values also reduces the probability of fire to the lowest level. According to the model result, if the probability of fire is *No*, low altitude values are another important variable that reduces the fire risk. According to the result, the probability of fire varies between 0.17 and 0.28. Especially at low altitudes, the probability of fire is minimized by low wind speed, which further increases the probability of fire (Table 6).

In the case of a *No* fire, high rainfall is one factor that significantly reduces the risk of fire. High precipitation increases the moisture content of the soil and vegetation and eliminates the conditions necessary for a fire outbreak. In areas with high rainfall, the probability of fire is at low levels. High precipitation amounts, especially in combination with low wind speed, also prevent fire spread and increase the probability that the fire will not occur. Likewise, low wind speeds also make the spread of fire difficult, increasing the likelihood that the fire will not start. Low wind speeds reduce the risk of fire outbreaks by preventing air movements favoring fire spread. When conditions such as low wind speed, temperature, or elevation are present, the probability of a fire not starting increases (Table 6).

The No fire occurrence scenario analysis shows that factors reducing fire risk play a significant role under certain combinations. Specifically, conditions such as low wind speed, high rainfall, and low temperature are the most important variables that increase the likelihood of no fire. Combining these factors significantly reduces fire risk and keeps the probability of fire non-occurrence within a wide range (between 0.17 and 0.43). Overall, the sensitivity analysis regarding the *No* fire scenario helps to understand how the fire's probability decreases due to various variables' interaction. These combinations highlight the conditions under which fire risk is lower, providing valuable insights for developing fire management strategies. Thus, through this analysis, it becomes clearer which variables should be focused on to minimize fire probability, enabling the creation of effective preventive strategies for fire risk management.

In general, the findings of the sensitivity analysis show that the interaction of factors affecting fire risk is quite complex and that the risk may increase with the combination of more than one variable. These combinations provide important data that must be analyzed to predict fire risk more accurately.

4.4 Fire risk analysis with BN-GIS integration

The fire risk map created for the study area is a significant output of the BN-GIS integration. This map visualizes the fire risk status of various environmental and spatial factors in the region in line with the variables determined for the study area. The spatial effects of land use, aspect, slope, elevation, population density, wind speed, temperature, and

precipitation shape fire risk distribution. The map has an increasing risk trend from green to red (Fig. 6).

According to the results, the following inferences can be drawn:

- The coastal areas of Muğla province are particularly the most prominent in terms of risk. Coastal districts such as Marmaris, Bodrum, Fethiye, and Datça are among the fire susceptible areas due to the density of forest areas, the length of hot and dry summer months, and population density. In these areas, it is evaluated that variables such as land use (density of forest areas), population density, distance to main roads, and slope play a determining role in fire probability. Increasing population density in densely forested areas, a dense road situation, and more sunlight on south-facing slopes increase the fire risk by increasing the temperature and decreasing humidity.
- Inland districts of Menteşe, Köyceğiz, Yatağan, Seydikemer, Dalaman, and Milas show different distributions in terms of fire risk compared to the coastal regions. Accordingly, Köyceğiz, inland areas of Dalaman and Ula districts, especially with their high forest areas, constitute fire risk areas, while land use variable affects these regions. Likewise, fire risk is also high around the forest areas around Milas, Yatağan, and Kavaklıdere. On the other hand, very high and bare mountainous areas located in the northeastern regions of Seydikemer district are the least risky areas. In such regions, the effect of height, slope, and bare area criteria come to the fore. The fire risk decreases in higher altitudes and sloping areas because of lower temperatures. In contrast, temperature and drought increase fire risk in low-altitude areas. Likewise, bare areas devoid of forest also reduce the fire risk.
- Menteşe, Kavaklıdere, and Seydikemer districts generally have relatively lower risk levels, and climatic factors and altitude variables limit fire risk in these regions. Since

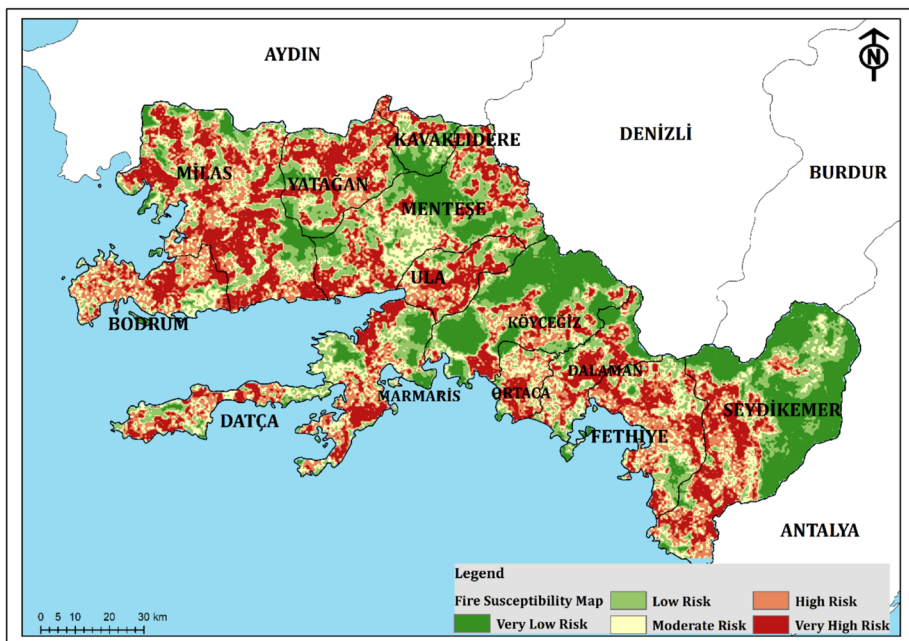


Fig. 6 Fire susceptibility map of the studied region

these districts are typically located at higher altitudes and have higher humidity, the fire risk is lower than that of coastal and forested areas. On the other hand, fire risk increases in some areas due to land use and population density variables in areas close to forest areas. This is evident in the map, with some sections' medium risk levels in light green and yellow tones.

- As a result, the fire risk distribution in Muğla province has been shaped by geographical characteristics, land use, population density, road conditions, climatic factors, and elevation. In summary, it is seen on the map that areas with dense forests and low altitudes are riskier in terms of fire, while the risk level is lower in high altitudes and humid regions. It has been determined that the risk of fire is higher in coastal areas due to the high population density, density of forest areas, high temperature, and drought effect. On the other hand, the regions formed by bare, high, and sloping mountainous regions have been determined as less risky areas.

5 Discussion

This study was compared with previous research regarding variable selection and analysis methods. The results indicate that variables such as aspect, slope, population density, elevation, and land use are key determinants of fire risk. According to the analysis, fire risk is particularly high in flat and moderately sloped areas and regions near forests and residential areas. Similarities and differences emerge when comparing the findings with previous studies on forest fire risk. For instance, Sevinc et al. (2020) emphasized temperature, precipitation, and land use as primary factors. In contrast, this study focuses on spatial and topographic variables such as aspect, slope, population density, elevation, land use, proximity to power lines, and distance to settlements. This distinction highlights how fire risk factors vary depending on geographical characteristics and data accessibility. Despite these differences, there are notable overlaps between the two studies. Sevinc et al. (2020) found that temperature increase, and anthropogenic factors significantly contribute to fire risk, while this study identifies flat lands, low slopes, and forested areas as critical fire-prone zones. Additionally, both studies acknowledge land use, population density, and distance to settlements as key determinants of fire risk. Sevinc et al. (2020) concluded that forested areas have a significantly higher fire risk, while areas with low population density experience a lower probability of fire. Their study also highlighted the impact of climatic variables on fire probability. Similarly, this study underscores the influence of land use, topographic, and climatic variables on fire probability. However, differences in variable selection and the study period have led to variations in the priority rankings of fire risk factors.

Another study by Dlamini (2010) utilized BN for forest fire risk analysis. This finding is consistent with the results of previous studies, key variables such as land use, elevation, average annual precipitation and temperature, aspect, and distance to settlements were emphasized. The findings indicated that areas covered by sugarcane, forests, and meadows have a high fire risk, whereas water bodies and bare surfaces exhibit a lower risk. The present study aligns with Dlamini's (2010) findings, as the variables influencing forest fire probability are relatively similar. Both studies highlight that fire risk is significantly higher in forested areas, reinforcing that dense vegetation and flammable materials play a crucial role in fire susceptibility.

Various studies have integrated forest fire risk with GIS and MCDM methods in the literature. For instance, Akbulak et al. (2018) developed a risk map for Çanakkale province.

The study used slope, elevation, aspect, distance to roads and settlement areas, and vegetation cover. Similar to the findings of this study, it was emphasized that fire risk increases in sloping areas, densely populated regions, and areas close to settlements. In another study, Çoban and Erdin (2020) similarly observed that population density and proximity to settlements significantly affect fire probability. The study particularly highlighted the role of human activities in escalating fire risk. Abedi Gheshlaghi (2019) also emphasized population density, land use, and proximity to settlement centers. His study underscored the strong correlation between fire risk and human-related variables. Akay and Şahin (2019) analyzed factors like slope, aspect, elevation, land use, and vegetation cover, demonstrating that topographic factors and vegetation density are crucial for understanding fire risk. These findings align with the results of the analyses in this study, supporting the conclusion that both human and environmental factors contribute significantly to fire risk.

This study, which focuses on forest fire susceptibility analysis, creates a fire risk map for Muğla province using the integration of Bayesian Networks (BN) and GIS. Noroozi et al. (2024) conducted a fire susceptibility analysis in Firouzabad, Iran, comparing the Random Forest (RF) and BN models. There are both similarities and differences between the two studies. While this study concentrates on the BN model, providing a more detailed analysis of spatial relationships and highlighting its ability to manage uncertainties, Noroozi et al. (2024) emphasized the high accuracy of the RF model. In this study, spatial analyses were used to evaluate factors such as slope, aspect, elevation, population density, and land use, whereas Noroozi et al. (2024) conducted a statistical analysis of different environmental variables' effects on fire risk using the RF model. Both studies provided practical methods for identifying fire risk areas. Although both the BN and RF models were successful in fire risk analysis, the BN model stands out as a powerful tool, particularly in identifying causal relationships between variables and managing uncertainty. Thus, the integration of BN with GIS and its spatial analysis capabilities in fire risk assessment set this study apart from similar studies in the literature, offering unique advantages in understanding the complex interactions influencing fire risk.

Building on the abovementioned discussion, the present study concludes that the findings obtained using the BN method in Muğla align with similar modeling approaches found in studies conducted in regions with varying geographical and climatic characteristics. However, results may differ depending on the unique characteristics of each area and the specific risk factors that hold significance. The study highlights the potential of the BN model to analyze the relationships between different variables in depth and to contribute to decision support systems through the integrated use of spatial data.

6 Conclusion

This study integrates GIS and BN to analyze fire-related parameters in the Muğla region, utilizing past fire location data. The BN model provides a valuable tool for understanding complex processes such as forest fires by analyzing various physical and human geographic variables. This approach enables statistical modeling of these variables' effects on fire risk, offering a clearer picture of their interrelationships. BN stands out particularly in managing uncertainty and providing decision-makers with insights into which variables most significantly influence fire risk. As such, the methodology used in this study proves to be a powerful tool for assessing fire risk probabilities.

GIS plays a critical role by overlaying each variable's data to determine the final fire risk. Integrating BN and GIS has further enhanced the analysis by allowing for a more coordinated examination of these critical data layers. This study identified eleven physical and human geographic variables and incorporated into the BN model using the GeNIe program. The probability values for these variables were calculated using ArcGIS's superimposition method. Data from the last five years of fires in the region were used to model the "Fire" event node, enabling the identification of factors influencing fire risk. Seven distinct scenarios were developed for analysis, including variations in land use (urban vs. forested areas), slope (flat vs. southern), and population density (high vs. low). Additionally, scenarios combining multiple variables—such as high population density, southern slopes, and forest areas—were explored. The fire risk map created in this study provides a detailed spatial distribution of fire-sensitive areas across Muğla province. The results indicated higher fire risk in coastal areas (such as Marmaris, Fethiye, Datça, and Bodrum), while inland areas with higher altitudes, steep slopes, and barren lands had lower fire risk. Key determinants of fire risk included slope, aspect, land use, population density, and climate variables. Notably, fire probability was higher in areas with southern slopes, low altitudes, and dense forest cover.

The study highlights land use, topographic features, climate conditions, and human activities as primary factors influencing fire risk in Muğla. Forested areas, in particular, are at high risk due to dense vegetation and dry weather conditions. Variables such as slope, wind speed, and direction determine the rate and direction of fire spread, with southern slopes and forested areas near settlements being especially susceptible. The study further emphasized that fire risk increases on flat terrains and low slopes, while population density, temperature, and land use were also significant contributors.

This research offers valuable insights for decision-makers and policymakers. By analyzing BN node values, it is possible to identify the most likely fire-contributing conditions, thereby enabling the implementation of preventative measures and reducing fire risk. The spatial fire risk map and variable analyses prepared within the scope of the study provide important data for decision-makers to develop forward-looking and effective risk mitigation strategies. Identifying high-risk areas, especially in coastal districts (such as Bodrum, Marmaris, Fethiye, and Datça), makes it possible to prioritize the allocation of watchtowers, rapid response teams, and additional extinguishing resources to these areas. The strong influence of slope, aspect, and land use on fire risk makes it necessary to increase protective forestry efforts and create fire lanes on southern slopes. Where forest and agricultural land are intertwined, awareness raising and inspections should be intensified to prevent stubble burning. In addition, the risk map can be used as a guide in zoning planning, and regulations such as restricting construction in high-risk areas or requiring safe construction standards can be made. Finally, organizing training and drills by local administrations and disaster response units focusing on high-risk districts will strengthen the measures that can be taken.

While the study offers considerable benefits, it does have some limitations. Its focus on a limited geographic area may restrict large-scale applications, and the temperature and precipitation data were estimated through methods like IDW and Kriging in ArcGIS. These approximations may not fully reflect localized variations. Additionally, the study used a small number of classes for certain variables, limiting the complexity of the BN model and optimizing computational efficiency. However, multiple scenarios were considered to enhance the reliability of the model's outputs, and the results were compared to similar studies in literature. Another limitation is that the node values were considered static, which may reduce the long-term predictive effectiveness, particularly in relation to

human-induced factors such as proximity to power lines, roads, and settlements. Future studies could address this limitation by using dynamic BN models that account for temporal changes.

Furthermore, additional parameters that affect fire risk in real life, such as time since the last fire, seasonality of fires, land ownership status, and human activities such as agriculture and tourism, can be integrated to improve the model's accuracy. However, it was impossible to include these parameters in the model in this study due to various limitations. A significant limitation was the lack of up-to-date, reliable, and continuous spatial data for variables such as the time since the last fire, the season of fires, and land ownership status. Obtaining such data often requires long-term field observations, access to archival resources, or costly data generation processes. In addition, since increasing the number of variables in the BN structure may lead to CPT overgrowth and a significant increase in computational burden, the number of variables has been deliberately limited to maintain model simplicity and computational efficiency. Therefore, these variables are considered potential inputs that can be evaluated in future studies. Including microclimatic factors and land management practices would offer a more comprehensive risk assessment. In future studies, incorporating machine learning and artificial neural networks could enhance the GIS-BN integration, creating a more robust and sensitive model.

Acknowledgement We would like to express our sincere gratitude to the Muğla Regional Directorate of Forestry for their support in providing the spatial datasets related to forest fires used in this study. Their contribution played a significant role in enabling the data-driven analyses conducted in this research.

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). The authors have not disclosed any funding.

Declarations

Conflict of interest The authors declare that they do not have a conflict of interest.

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References

- Abedi Gheshlaghi H (2019) Using GIS to develop a model for forest fire risk mapping. *J Indian Soc Remote Sens* 47(7):1173–1185. <https://doi.org/10.1007/s12524-019-00981-z>
- Adab H, Kanniah KD, Solaimani K (2013) Modeling forest fire risk in northeast Iran using remote sensing and GIS techniques. *Nat Hazards* 65:1723–1743. <https://doi.org/10.1007/s11069-012-0450-8>
- Akay AE, Şahin H (2019) Forest fire risk mapping by using GIS techniques and AHP method: a case study in Bodrum (Turkey). *Eur J for Eng* 5(1):25–35. <https://doi.org/10.33904/ejfe.579075>
- Akbulak C, Tatlı H, Aygün G, Sağlam B (2018) Forest fire risk analysis via integration of GIS, RS and AHP: The Case of Çanakkale, Turkey. *J Human Sci* 15(4):2127–2143
- Almeida B, Cabral P, Fonseca C, Gil A, Scemama P (2024) Top 10+1 indicators for assessing forest ecosystem conditions: a five-decade fragmentation analysis. *Sci Total Environ* 957:177527. <https://doi.org/10.1016/j.scitotenv.2024.177527>

- Ames D, Anselmo A (2008) Bayesian network integration with GIS. In: Shekhar S, Xiong H (eds) Encyclopedia of GIS. Springer, Boston
- Arroyo-Figueroa G, Sucar LE (2013) A temporal Bayesian network for diagnosis and prediction. arXiv preprint [arXiv:1301.6675](https://arxiv.org/abs/1301.6675). <https://doi.org/10.48550/arXiv.1301.6675>
- Atalay İ (1994) Vegetation geography of Türkiye. Ege University Press, İzmir
- Atmaca İ, Derakhshandeh M, Işık-Pekkan Ö et al (2022) Forest fire risk modeling using logistic regression and geographic information systems: a case study in Muğla—Milas. *J Nat Hazards Environ* 8(1):66–75. <https://doi.org/10.21324/dacd.951902>
- Ballari D, Wachowicz M, Bregt AK, Manso-Callejo M (2012) A mobility constraint model to infer sensor behaviour in forest fire risk monitoring. *Comput Environ Urban Syst* 36(1):81–95. <https://doi.org/10.1016/j.compenvurbsys.2011.06.004>
- Brooks ML, Matchett JR (2006) Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. *J Arid Environ* 67:148–164. <https://doi.org/10.1016/j.jaridenv.2006.09.027>
- Cetin M, Isik Pekkan Ö, Ozenen Kavlak M et al (2023) GIS-based forest fire risk determination for Milas district. *Turkey Nat Hazards* 119(3):2299–2320. <https://doi.org/10.1007/s11069-022-05601-7>
- Coban H, Erdin C (2020) Forest fire risk assessment using GIS and AHP integration in Bucak forest enterprise, Turkey. *Appl Ecol Environ Res* 18(1):1567–1583
- Coşkun M, Toprak F (2023) Geographical information systems (GIS) based forest fire risk analysis: case of Bartin. *Geomatik* 8(3):250–263. <https://doi.org/10.29128/geomatik.1192219>
- Darkot B, Tuncel M (1978) Geography of the Aegean Region. Istanbul University Geography Institute Publication No: 99, İstanbul (in Turkish)
- Das J, Mahato S, Joshi PK, Liou YA (2023) Forest fire susceptibility zonation in Eastern India using statistical and weighted modelling approaches. *Remote Sens* 15(5):1340. <https://doi.org/10.3390/rs15051340>
- Demirel H, Başhan V, Yucesan M, Gul M (2024) A comprehensive risk assessment framework for mooring risks at hydrocarbon berths using fuzzy rule-based Bayesian network and multi-attribute decision-making. *Stoch Environ Res Risk Assess* 38:4393–4414. <https://doi.org/10.1007/s00477-024-02809-w>
- Dlamini MW (2010) A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. *Environ Model Softw* 25(2):199–208. <https://doi.org/10.1016/j.envsoft.2009.08.002>
- Erol O (1991) Abandoned historical harbors on Turkish coastline and the impact of coastal changes as an environmental problem. *Bull Inst Mar Sci Geogr Istanbul Univ* 8:1–45 ((In Turkish))
- Eugenio FC, dos Santos AR, Fiedler NC, Ribeiro GA, da Silva AG, dos Santos AB et al (2016) Applying GIS to develop a model for forest fire risk: a case study in Espírito Santo, Brazil. *J Environ Manag* 173:65–71. <https://doi.org/10.1016/j.jenvman.2016.02.021>
- Falk DA, Miller C, McKenzie D, Black AE (2007) Cross-scale analysis of wildfire regimes. *Ecosystems* 10:809–823. <https://doi.org/10.1007/s10021-007-9070-7>
- Forest Fire Fighting Department. <https://www.ogm.gov.tr/muglaobm/duyurular/mugla-obm-2023-yili-yangin-degerlendirme-raporu> (In Turkish)
- Forest Fires Assessment Report (2023). Muğla Forest Regional Directorate
- Ganteaume A, Camia A, Jappiot M et al (2013) A review of the main driving factors of forest fire ignition over Europe. *Environ Manag* 51:651–662. <https://doi.org/10.1007/s00267-012-9961-z>
- Grêt-Regamey A, Straub D (2006) Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS. *Nat Hazards Earth Syst Sci* 6(6):911–926. <https://doi.org/10.5194/nhess-6-911-2006>
- Gürsoy Mİ, Orhan O, Tekin S (2023) Creation of wildfire susceptibility maps in the Mediterranean Region (Turkey) using convolutional neural networks and multilayer perceptron techniques. *For Ecol Manag* 538:121006. <https://doi.org/10.1016/j.foreco.2023.121006>
- Hong H, Tsangaratos P, Ilia I et al (2018) Applying genetic algorithms to set the optimal combination of forest fire related variables and model forest fire susceptibility based on data mining models: the case of Dayu County. *China Sci Total Environ* 630:1044–1056. <https://doi.org/10.1016/j.scitotenv.2018.02.278>
- <https://pro.arcgis.com/en/pro-app/latest/tool-reference/analysis/pairwise-intersect.htm>
- İkiel C (2004) Book of Muğla (Archaeology, History, Geography). In: Çınar AA (ed) Geographical features of Muğla. T.C. Muğla Governorship, Muğla-İzmir, pp 15–25
- Jaiswal RK, Mukherjee S, Raju KD, Saxena R (2002) Forest fire risk zone mapping from satellite imagery and GIS. *Int J Appl Earth Obs Geoinf* 4(1):1–10. [https://doi.org/10.1016/S0303-2434\(02\)00006-5](https://doi.org/10.1016/S0303-2434(02)00006-5)
- Jolly WM, Cochrane MA, Freeborn P et al (2015) Climate-induced variations in global wildfire danger from 1979 to 2013. *Nat Commun* 6:7537. <https://doi.org/10.1038/ncomms8537>
- Kalacska M, Sánchez-Azofeifa GA, Caelli T et al (2005) Estimating leaf area index from satellite imagery using Bayesian belief networks. *IEEE Trans Geosci Remote Sens* 43(8):1866–1873. <https://doi.org/10.1109/TGRS.2005.848412>

- Konurhan Z, Yucesan M, Gul M (2023) Integrating stratified best–worst method and GIS for landslide susceptibility assessment: a case study in Erzurum province (Turkey). *Environ Sci Pollut Res* 30:113978–114000. <https://doi.org/10.1007/s11356-023-30200-9>
- Leuenberger M, Parente J, Tonini M et al (2018) Wildfire susceptibility mapping: deterministic vs. stochastic approaches. *Environ Model Softw* 101:194–203. <https://doi.org/10.1016/j.envsoft.2017.12.019>
- Lu Y, Zhai G, Zhou S (2024) An integrated Bayesian networks and geographic information system (BNs-GIS) approach for flood disaster risk assessment: a case study of Yinchuan. *China Ecol Indic* 166:112322. <https://doi.org/10.1016/j.ecolind.2024.112322>
- Marcot BG, Penman TD (2019) Advances in Bayesian network modelling: integration of modelling technologies. *Environ Model Softw* 111:386–393. <https://doi.org/10.1016/j.envsoft.2018.09.016>
- Marcot BG, Stevenot JD, Sutherland GD, McCann RK (2006) Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. *Can J for Res* 36:3063–3074. <https://doi.org/10.1139/x06-135>
- Mihunov VV, Lam NS (2020) Modeling the dynamics of drought resilience in South-Central United States using a Bayesian network. *Appl Geogr* 120:102224. <https://doi.org/10.1016/j.apgeog.2020.102224>
- Mouillot F, Ratte JP, Joffre R et al (2003) Some determinants of the spatio-temporal fire cycle in a Mediterranean landscape (Corsica, France). *Landscape Ecol* 18:665–674. <https://doi.org/10.1023/B:LAND.0000004182.22525.a9>
- Myers B, Allan G, Bradstock R, Dias L, Duff G, Jacklyn P, Landsberg J, Morrison J, Russell-Smith J, Williams R (2004) Wildfire management in the rangelands. Tropical Savannas CRC, Darwin
- Noroozi F, Ghanbarian G, Safaeian R, Pourghasemi HR (2024) Forest fire mapping: a comparison between GIS-based random forest and Bayesian models. *Nat Hazards* 120:6569–6592. <https://doi.org/10.1007/s11069-024-06457-9>
- Nuthammachot N, Stratoulis D (2021) Multi-criteria decision analysis for forest fire risk assessment by coupling AHP and GIS: method and case study. *Environ Dev Sustain* 23:17443–17458. <https://doi.org/10.1007/s10668-021-01394-0>
- Parajuli A, Gautam AP, Sharma SP et al (2020) Forest fire risk mapping using GIS and remote sensing in two major landscapes of Nepal. *Geomatics Nat Hazards Risk* 11(1):2569–2586. <https://doi.org/10.1080/19475705.2020.1853251>
- Pollino CA, Woodberry O, Nicholson A, Korb K, Hart BT (2007) Parameterisation and evaluation of a Bayesian belief network for use in an ecological risk assessment. *Environ Model Softw* 22:1140–1152. <https://doi.org/10.1016/j.envsoft.2006.03.006>
- Salehi N, Dashti S, Roshan SA et al (2023) Using neural networks and a fuzzy inference system to evaluate the risk of wildfires and the pinpointing of firefighting stations in forests on the northern slopes of the Zagros Mountains, Iran (case study: Shimbar national wildlife preserve). *Environ Monit Assess* 195:294. <https://doi.org/10.1007/s10661-022-10702-8>
- San-Miguel-Ayanz J, Durrant T, Boca R et al (2021) Advance EFFIS report on forest fires in Europe, Middle East and North Africa 2020, EUR 30693 EN. Publications Office of the European Union, Luxembourg. ISBN 978-92-76-37557-9. <https://doi.org/10.2760/344684>. JRC124833.
- Sevinc V, Kucuk O, Goltas M (2020) Bayesian network model for prediction and analysis of possible forest fire causes. *Forest Ecol Manag* 457:117723. <https://doi.org/10.1016/j.foreco.2019.117723>
- Sivrikaya F, Küçük Ö (2022) Modeling forest fire risk based on GIS-based analytical hierarchy process and statistical analysis in Mediterranean region. *Ecol Inform* 68:101537. <https://doi.org/10.1016/j.ecoinf.2021.101537>
- Spiegelhalter DJ, Dawid AD, Lauritzen SL, Cowell RG (1993) Bayesian analysis in expert systems. *Stat Sci* 8:219–283
- Sun S, Zhang C, Yu G (2006) A Bayesian network approach to traffic flow forecasting. *IEEE Trans Intell Transp Syst* 7(1):124–132. <https://doi.org/10.1109/TITS.2006.869623>
- Tien Bui D, Bui QT, Nguyen QP et al (2017) A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area. *Agric for Meteorol* 233:32–44. <https://doi.org/10.1016/j.agrformet.2016.11.002>
- Trucchia A, Meschi G, Fiorucci P et al (2022) Defining wildfire susceptibility maps in Italy for understanding seasonal wildfire regimes at the national level. *Fire* 5(1):30. <https://doi.org/10.3390/fire5010030>
- Wang Y, Vassileva J (2003) Bayesian network-based trust model. In: Proceedings IEEE/WIC international conference on web intelligence (WI 2003). IEEE, pp 372–378. <https://doi.org/10.1109/WI.2003.1241218>
- Yang X, Jin X, Zhou Y (2021) Wildfire risk assessment and zoning by integrating maxent and GIS in Hunan province. *China for* 12:1299. <https://doi.org/10.3390/f12101299>
- Yılmaz İ, Öztürk D (2019) Integration of GIS and Bayesian networks in spatial planning and decision problems: Forest fire hazard assessment. In: Proceedings of the 6th Geographic Information Systems Congress of TMMOB, Ankara, Turkey, 23–25.

- Zhang Y, Teoh BK, Zhang L (2022) Integrated Bayesian networks with GIS for electric vehicles charging site selection. *J Clean Prod* 344:131049. <https://doi.org/10.1016/j.jclepro.2022.131049>
- Zwirlmaier K, Papakosta P, Štraub D (2013) Learning a Bayesian network model for predicting wildfire behavior. In: Smith J (ed) *Safety, reliability, risk and life-cycle performance of structures and Infrastructures*. CRC Press

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