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Road network connectivity explains wildfire probability in Southern Italy

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ABSTRACT

Wildfire ignition and spread are strongly influenced by anthropogenic factors, particularly road networks. This study investigated the relationship between road network connectivity and wildfire probability in the Apulia region of southern Italy. A wildfire probability map was developed using an Artificial Neural Network (ANN) model, incorporating wildfire occurrence data from 2000 to 2021, along with landscape, climatic, and topographic variables. The resulting probability map was classified into three categories: High Wildfire Probability (HWP), Medium Wildfire Probability (MWP), and Low Wildfire Probability (LWP). Cochran's formula was used to calculate the required sample size, and Neyman allocation was applied to ensure optimal stratified sampling across probability categories.

Connectivity indices were then estimated for each sampled area and statistically analyzed using the Kruskal-Wallis test. Results indicated that the majority of the study area fell within the LWP category (65.69 %), followed by MWP (21.48 %) and HWP (12.83 %). Statistically significant differences were observed across all categories for key connectivity indices. HWP areas exhibited higher road density, node counts, and number of links, reflecting more complex and interconnected road networks. In contrast, LWP areas showed lower connectivity and simpler network structures. The Alpha, Gamma, and Eta indices in particular displayed marked variation, with HWP zones exhibiting significantly higher values. These findings highlight the dual role of road networks: while they are vital for wildfire suppression and evacuation, their increased presence and complexity may elevate ignition risk due to greater human activity in densely connected areas.

1. Introduction

In human systems, road networks are widely recognized as critical infrastructure that fosters rapid and sustained development (Capacci et al., 2022; Pan et al., 2024). They play a central role in promoting economic growth, enhancing social connectivity, and enabling the efficient movement of goods and people,contributing significantly to the advancement of societies (Chen et al., 2024; Petrosillo et al., 2013; Rivera-Royero et al., 2022) as well as influencing natural and semi-natural ecosystems (Pablo-Martí et al., 2021; Loreti et al., 2022; Chen et al., 2024; Jana et al., 2025). In this context, the road network, as a human-made structure embedded within forest landscapes, can be considered a major component of forest ecosystems—capable of exerting both positive and negative effects on wildfire occurrence (Kuklina et al., 2023; Zambon et al., 2019).

A substantial body of international research has examined the relationship between roads and wildfires (Narayanaraj and Wimberly, 2012; Mostafa et al., 2017; Elia et al., 2019; Hong et al., 2019; Mostafa et al., 2024; He et al., 2024). For instance, (Arienti et al., 2009) found a direct correlation between road density and wildfire activity in the Canadian western boreal forest. Similarly, in California, Narayanaraj and Wimberly (2012) observed that wildfire ignitions were concentrated near roads in areas with high road density, whereas lightning-caused fires were more prevalent in remote areas with low road density (Shi et al., 2018; Gunawan et al., 2024). In Southern Italy, Mostafa et al. (2024) reported a positive association between road density and fire ignition frequency. However, they also found that higher road density may reduce wildfire extent, likely due to reduced fuel continuity and improved access for suppression. By contrast, He et al. (2024) observed a lower influence of road proximity on wildfire risk in China, whereas

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[Zambon et al. (2019)](#) highlighted that over 50 % of wildfires in Spain occurred near local and municipal roads.

This literature reveals a clear pattern of contrasting results regarding the role of roads in wildfire occurrence. We argue that the reliance on a limited set of metrics primarily road density and proximity to roads fails to capture the complex and multifaceted relationship between road networks and wildfire dynamics. A broader set of topological indices, often overlooked in current research, may provide a more nuanced and comprehensive understanding of this relationship. Incorporating diverse road network connectivity metrics into fire risk assessments and infrastructure planning could significantly improve our ability to interpret, anticipate, and mitigate wildfire events.

To fill this gap, the objective of this study is to examine how multiple road network connectivity indices (including Alpha, Beta, Gamma, Cyclomatic Number, and Eta) relate to wildfire probability across distinct risk categories (low, medium, and high). By identifying significant differences in these indices among wildfire probability zones within the Apulia region (Southern Italy), we aim to reveal the structural network patterns that influence wildfire dynamics. This methodological framework can be applied to similar contexts, offering a comprehensive approach beyond conventional metrics such as road density alone. While our findings in Apulia provide valuable insights, their significance is secondary to the broader methodological approach we propose. The strength of this study lies in the transferable framework for analyzing the relationship between road network topology and wildfire probability an approach that can be applied to other regions facing similar challenges.

2. Materials and methods

2.1. Study area

Apulia represents the easternmost region in Italy, located between latitudes 39°50′–41°50′N and longitudes 15°50′–18°50′E. It encompasses a total area of approximately 19,532 km2 (Fig. 1). The landscape of this region is Mediterranean, primarily consisting of agricultural land, with the major land covering olive gardens and vineyards. Additionally, approximately 14 % of the region is covered by forests, woodlands, and Maquis. The climate is characterized by mild, rainy winters, hot and dry summers, and a significant water deficit from June to September. The annual rainfall ranges from 450 to 650 mm, with the majority occurring in the winter. The mean annual temperature ranges from 12 °C in mountainous areas to 19 °C along the southern coasts. Maximum temperatures often exceed 34 °C during the summer season (Elia et al., 2015). The total road network length in the Apulia region is about 33,381 km, consisting of national and regional highways as well as local and forest roads. This dataset was derived from a local project.

The following is an outline of the workflow, referring to the methodology applied in this study (Fig. 2).

2.2. Data collection and processing

2.2.1. Wildfire mapping

The estimation of wildfire occurrence probability requires building a set of explanatory variables according to their potential relationship to the response variable. Therefore, we used the number of wildfire events and burnt areas in the Apulia region from 2000 to 2021 as response

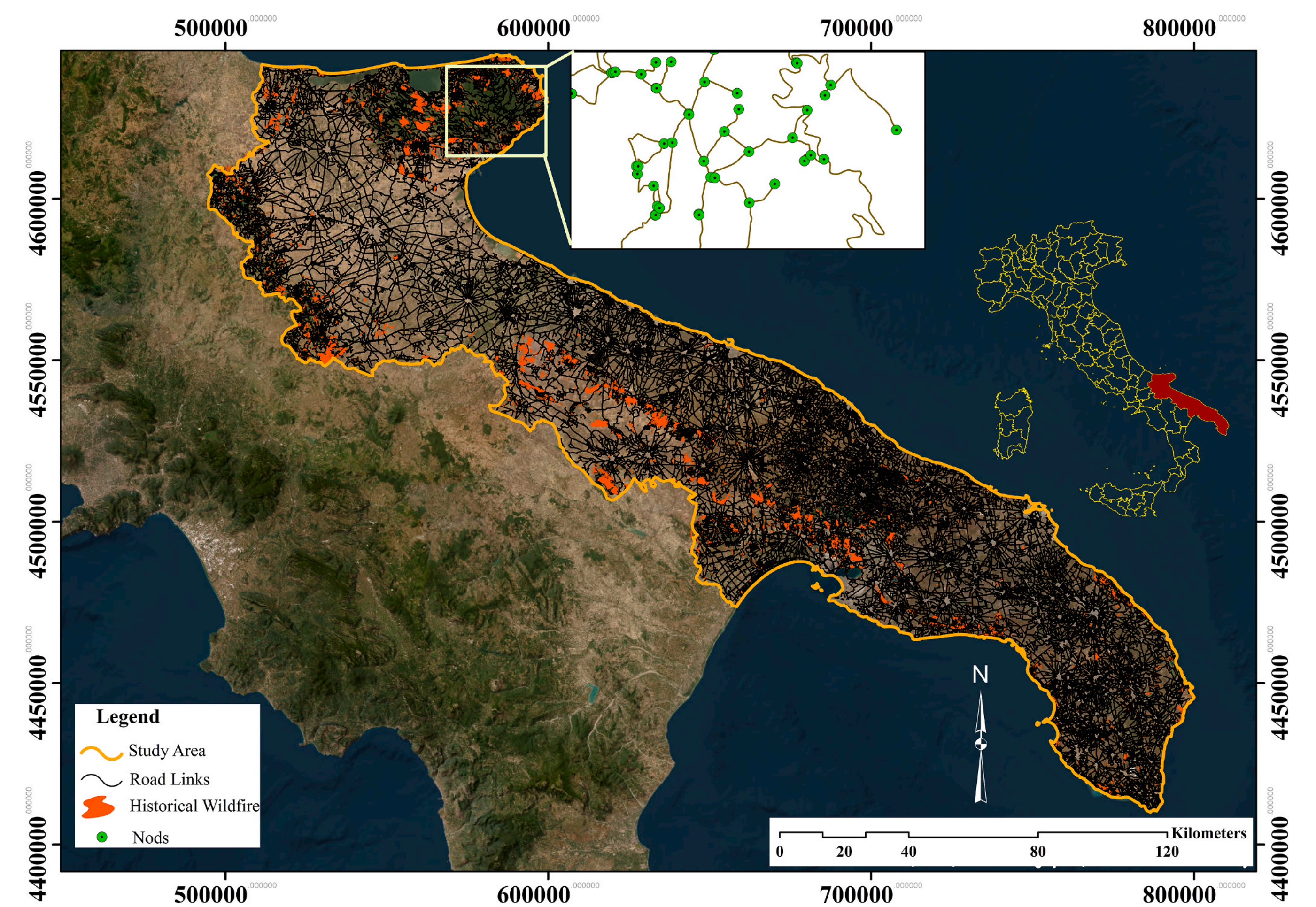

Fig. 1. Distribution of historical wildfires and the road network within the study area (Apulia region, Southern Italy).

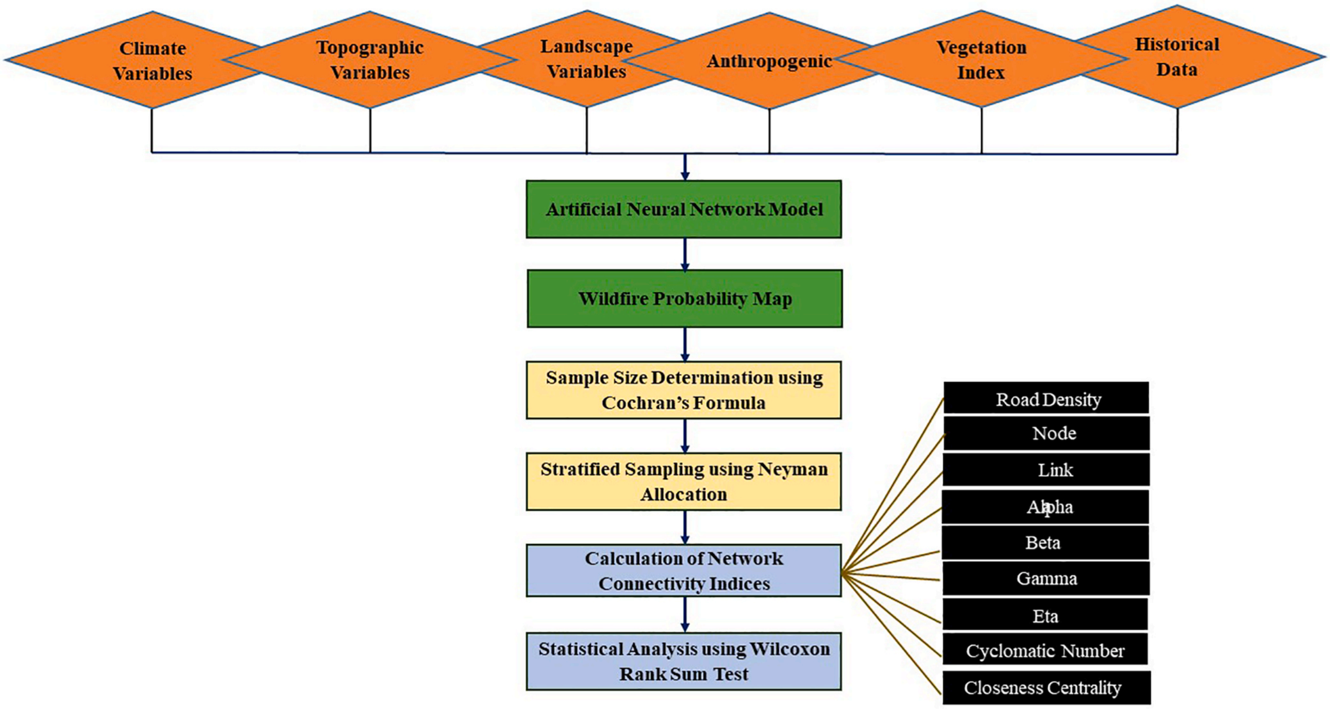

Fig. 2. Workflow of the overall study methodology.

variables (Elia et al., 2022). The dataset was derived from the Geoportale Nazionale (https://gn.mase.gov.it/portale/en/web/geoportale-mase/fires) (Access: 12/11/2024). We applied landscape, climate, vegetation index, and topographic factors as explanatory variables at a 1-km^2 grid resolution (Table S1). The machine learning model used in the study is the Artificial Neural Network (ANN), which is widely used in wildfire sciences and commonly shows high model performance (Aldersley et al., 2011; Elia et al., 2020; Jain et al., 2020; Zhang et al., 2021).

2.2.2. Sample size allocation

In statistical analysis, accurate sample size determination is crucial for ensuring the validity and reliability of results. One widely used method for sample size calculation is Cochran's formula (Eq. (1), particularly effective for estimating proportions in large populations (Cochran, 1977; Yang and Kim, 2020).

$$n = \frac{NZ^2p(1-p)}{E^2(N-1)+Z^2p(1-p)} \tag{1}$$

where n indicates the sample size, N is the population size, Z represents the Z-score (1.96 for 95 % variability), and E represents the desired margin of error (e.g., 0.05 for 5 %). This study applies Cochran's formula to determine the sample size for analyzing wildfire road connectivity across three probability categories: High Wildfire Probability (HWP); Medium Wildfire Probability (MWP); and Low Wildfire Probability (LWP). Stratified sampling ensures that each category is adequate where n indicates the sample size, N is the population size, Z represents the Z-score (1.96 for 95 %. variability), and E represents the desired margin of error (e.g., 0.05 for 5 %). This study applies Cochran's formula to determine the sample size for analyzing wildfire road connectivity across three probability categories: High Wildfire Probability (HWP); Medium Wildfire Probability (MWP); and Low Wildfire Probability (LWP). Stratified sampling ensures that each category is adequately represented, providing a comprehensive understanding of connectivity and its implications on wildfire management.

In survey sampling and statistical analysis, determining the optimal allocation of samples across different strata (subgroups) is crucial for enhancing the precision and efficiency of estimates. Neyman allocation is a technique used for this purpose, ensuring that the sample size is proportionally distributed based on the variability within each stratum (Arunachalam and Spence, 2023; Neyman, 1992; Tillé and Favre, 2005); see Eq. (2).

$$n_i = \frac{N_iS_i}{\sum_J^L N_iS_i} n \tag{2}$$

N_i is the Population size (proportional area) for category i, S_i is the Standard deviation of wildfire probability for category i, n represents Total sample size, and n_i stands for Sample size for category i.

When combined with Cochran's formula, Neyman allocation provides an effective strategy for determining and distributing sample sizes in stratified sampling. This method enhances the precision and accuracy of statistical estimates by ensuring optimal representation and minimizing overall variance (Lohr, 2019; Wright, 2020; Thompson et al., 2021; Han et al., 2024). In the context of wildfires, road connectivity allows for a detailed and reliable analysis of connectivity factors across different wildfire probability categories, aiding in more effective wildfire management and decision-making.

2.3. Measures and indices

Alpha (α) (Circuitry): The Alpha index, which measures the degree of connectivity and circuitry within the network, evaluates the ratio of the actual number of cycles to the maximum number of cycles in the network. The higher the Alpha index, the more connected a network is. Simple networks have a value of 0, while a value of 1 indicates a completely connected network. This index measures the level of connectivity independently of the number of nodes (Rodrigue et al., 2016; Wong et al., 2020). Negative values can be derived when a network has a very low level of circuitry (Haggett, 1977; Kofi, 2010). The Alpha (α) index is given in Eq. (3).

$$\alpha = \frac{e-v+1}{2v-5} \tag{3}$$

e is the Number of links (edges) and v is the Number of nodes (Vertex).

Beta (β) (Connectivity): Measures the level of connectivity in a graph and is expressed by the ratio of the number of links (e) to the number of nodes (v). A Beta (β) value less than 1 indicates a disconnected network (e.g., a tree pattern), a connected network with one cycle has a value of 1, and a Beta (β) value greater than 1 implies a more connected network (Patarasuk, 2013; Rodrigue et al., 2016; Cabrera et al., 2024) Eq. (4).

$$\beta = \frac{e}{v} \tag{4}$$

Gamma (γ) (Completeness): Measures the ratio of the actual number of links to the maximum number of links possible in the network (Rojnkureesatien, 2006; Rodrigue et al., 2016). Gamma index values range between 0 and 1 (or percentages); a value of 1 denotes a completely connected network (Patarasuk, 2013) Eq. (5).

$$\gamma = \frac{e}{3(v-2)} \tag{5}$$

Cyclomatic Number (μ) (Redundancy and Complexity): The Cyclomatic Number reflects the network's redundancy and complexity. A higher value indicates a higher degree of complexity (Liu and Zhao, 2015; Sarkar et al., 2020) (Eq. (6)).

$$\mu = \mathrm{e} - \mathrm{v} + p \tag{6}$$

p is the number of non-connected graphs.

Eta (η) (Efficiency): The Eta index (η) indicates the average length per link, reflecting the network's efficiency. It is used as a measure of speed in a traffic network. Adding new nodes will cause a decrease of the Eta index as the average length per link declines. The Eta index is shown in Eq. (7) (Nagne et al., 2013; Sreelekha et al., 2016; Mostafa et al., 2023),

$$\eta = \frac{L(G)}{e} \tag{7}$$

$L(G)$ is the Summation of all links in the network.

2.4. Statistical approach

The statistical analysis was conducted using R software. The Kolmogorov-Smirnov and Shapiro-Wilk tests for normality were applied to determine the appropriate type of statistical tests for this study. The Kruskal-Wallis test was performed to compare network connectivity indices among wildfire probability categories (Patarasuk, 2013). The test evaluates whether there are statistically significant differences between the medians of three or more independent groups Eq. (7) (Guo et al., 2013).

$$H = \frac{12}{N(N+1)}\sum_{i=1}^{k}\frac{R_i^2}{n_i} - 3(N+1) \tag{8}$$

Where N is the total number of values in all samples; ni is the number of values contained in the ith sample, and Ri is the sum of ranks in ith sample.

The Kruskal-Wallis test results help evaluate the separability of each classification level based on a given index-parameter combination. We considered a p-value > 0.05 as significant. In such cases, a post hoc Dunn's test with a Benjamini-Hochberg adjustment was conducted to identify which wildfire probability category showed a significant difference (Akanga et al., 2022; Shi et al., 2025). We selected the Kruskal-Wallis (KW) test and post hoc Dunn's test over the more commonly used Analysis of Variance (ANOVA) and post hoc t-test because most of network connectivity indices did not follow a normal distribution across the study area.

3. Results

3.1. Wildfire probability mapping and road network Characterization

In this study, the predictive variables were checked and selected based on their highest predictive utility to build an ANN model that estimates wildfire probability. The Root Mean Square Error (RMSE) value of 0.79 on the validation dataset indicates that the model has a reasonable level of accuracy in predicting wildfire probability. This relatively low RMSE value demonstrates the model's ability to generalize well beyond the training dataset, suggesting its effectiveness in estimating wildfire probability in different regions. The high classification accuracy and strong performance of ANNs suggest that our model can be effectively used to estimate wildfire probability in our study area. The wildfire probability ranges from 0 to 1. To facilitate analysis, this range was classified into three equal categories LWP, MWP, and HWP. The results indicate that the LWP category is the largest on the wildfire probability map (65.69 %), followed by the MWP category (21.48 %), and the HWP category (12.83 %) (Fig. 3). The wildfire probability map (Fig. 3) shows a high probability of wildfire occurrence throughout the entire Gargano territory in the north of Apulia where one of the largest wildfires in the region occurred in 2007. Even the Daunian Sub-Apennine in the northwest and the central part of the Apulia region show high wildfire probability.

The wildfire probability ranges from 0 to 1. To facilitate analysis, this range was classified into three equal categories: Low Wildfire Probability (LWP), Medium Wildfire Probability (MWP), and High Wildfire Probability (HWP). The results indicate that the LWP category is the most dominant on the wildfire probability map, covering 65.69 % of the area, followed by the MWP category at 21.48 % and the HWP category at 12.83 % (Fig. 3). The wildfire probability map highlights a high probability of wildfire occurrence in the Gargano territory in northern Apulia, where one of the region's largest wildfires occurred in 2007, as well as in the Daunian Sub-Apennine in the northwest and the central part of the Apulia region.

3.1.1. Sample size allocation

The allocation proportions for the Neyman allocation method are displayed in Table 1 and Fig. 4. The LWP category represents the largest proportion of the sample size, with 66 % (1016 samples) allocated, reflecting the higher proportion of the low probability category in the overall population and ensuring that sufficient data are collected for accurate estimation of wildfire probabilities. The MWP category received 21 % (381 samples) of the total allocated samples, allowing for precise estimation of wildfire probability within this category.

The HWP category constitutes the smallest proportion of the sample size (13 %) (124 samples). However, this allocation still ensures adequate representation of the high-probability category, allowing for reliable estimates of wildfire probability. The area of each sample, estimated using Cochran's formula, was approximately 385 ha.

3.2. Assessment of road network indices across wildfire probability categories

The distribution of indices across the three categories HWP, MWP, and LWP are presented in Fig. 5. The values for Alpha are close to zero for all probability categories. There are outliers, particularly in the low probability class. The distributions of Beta across all classes are similar, indicating minimal variation among probability categories. The Cyclomatic number decreases as the probability class moves from LWP to HPW. The Eta value shows a gradual decrease as the probability of wildfire increases. Gamma values are relatively stable across probability classes with minor variations. The number of links increases significantly in the HWP compared to the LWP. The number of nodes increases from LWP to HWP, indicating that higher probability classes may be associated with a greater number of nodes. Road density shows an

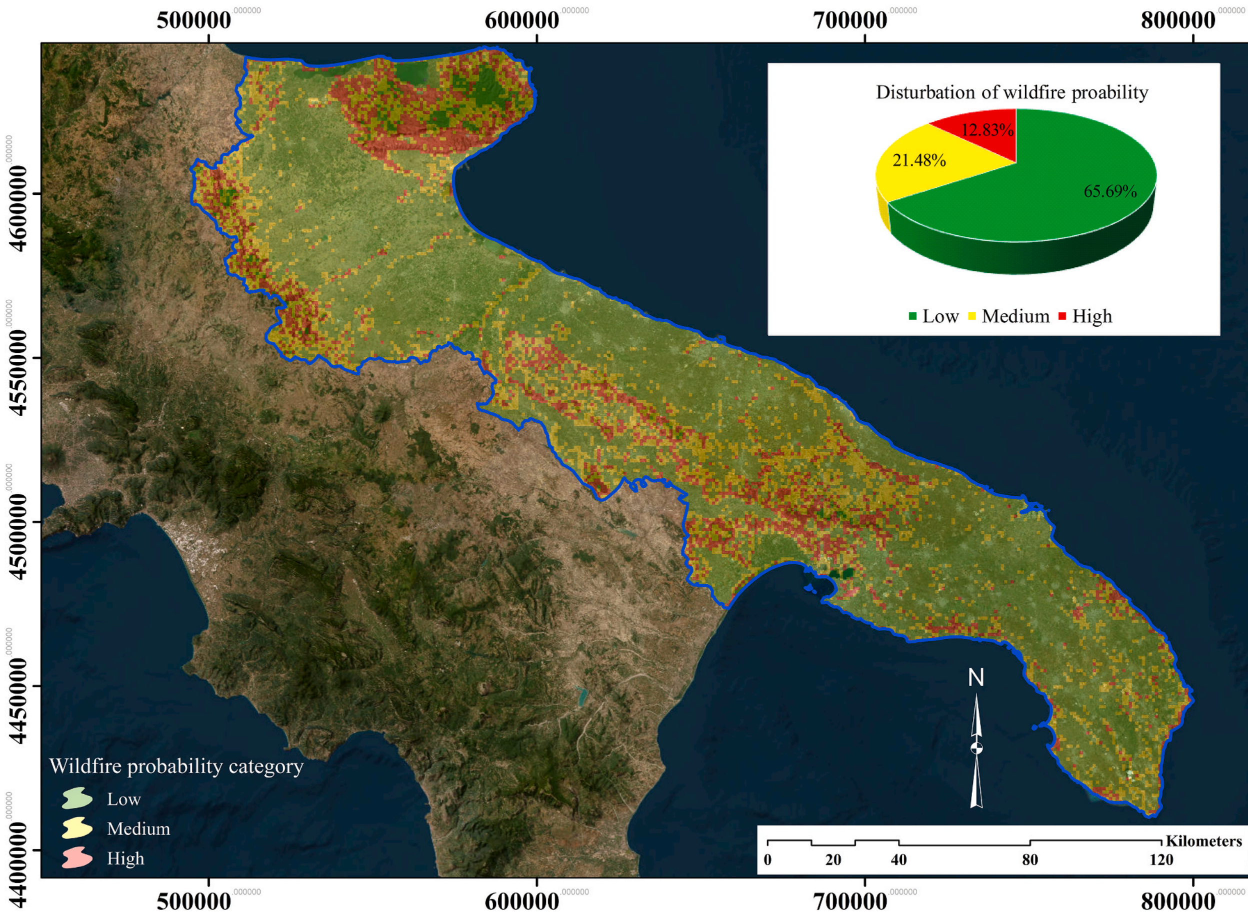

Fig. 3. Wildfire probability map by the Artificial Neural Network model. This map illustrates the spatial distribution of wildfire probability in the Apulia region: low (green), medium (yellow), and high (red) probability. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Sample size allocation proportion for each wildfire probability category.

Wildfire probability Category	Proportion	Sample size
Low	0.66	1016
Medium	0.21	381
High	0.13	124

increasing trend from Low to High, indicating that areas with higher road density tend to have a greater probability of wildfires.

The network connectivity indices associated with LWP are summarized in Table 2. This table includes key metrics such as the value of wildfire probability, road density, number of nodes, number of links, Alpha, Beta, Gamma, Eta and Cyclomatic Number. For instance, Sample Area 1 (SA1) demonstrated a wildfire probability of 0.27 with a road density of 54.2 km/km^2, while Sample Area 2 (SA2) showed a lower wildfire probability of 0.16 and a road density of 19.32 km/km^2. The range of road density in this category is 0 to 70.47 m/ha. The maximum number of nodes in this category is 102, while the minimum number of nodes is 0. More nodes generally indicate a more complex network with more intersections or endpoints. The number of links in this category are between 0 and 96 (Table 2). The Alpha values provided for this category showed a range of negative to zero values. Most values were negative, ranging from −3 to −0.01. These values indicate networks that lack redundancy and are less complex. A single value of 0 was observed, suggesting a network with minimal complexity but still connected. High Beta values (e.g., 1.33, 1, 0.9) indicate well-connected networks with more links per node, which are typically better equipped for handling emergencies and evacuations due to their higher connectivity. Conversely, low Beta values (e.g., 0, 0.22, 0.37) signify less connected networks with fewer links relative to the number of nodes (Table 2). The range of Gamma values was 0–1. Higher values reflect networks with more cycles relative to their links and nodes, indicating greater complexity and redundancy. Lower values indicate networks with fewer cycles and lower complexity, indicating they might be simpler and less redundant (Table 2). In the low category the Cyclomatic Number achieved negative, zero and positive values; nevertheless, these values were mostly negative. Therefore, this result indicates networks that lack sufficient connections, are potentially disconnected, or fragmented.

Table 3 presents the network connectivity indices for the MWP category. It details essential metrics including wildfire probability, road density, number of nodes, number of links, and various connectivity metrics such as Alpha, Beta, Gamma, Eta, and Cyclomatic number. For instance, Sample Area 3 (SA3) revealed a wildfire probability of 0.43 and a Beta index of 0.62, while Sample Area 379 (SA379) showed a slightly lower wildfire probability of 0.40 and Beta index of 0.83. The minimum road density recorded in the MWP category was 0, while the maximum road density reached was 65.24. Notably, four samples exhibited a road density of 0, indicating areas with no measurable road infrastructure. The recorded number of nodes ranged from a minimum of 0 to a maximum of 149 in the MWP category. A notable observation is that some samples exhibited a node count of 0, indicating areas with no significant connectivity or infrastructure. In contrast, certain sample areas demonstrated a high number of nodes, reaching up to 149, which reflects more complex network structures. The number of links in the MWP category ranged from 0 to 148. In some samples the number of

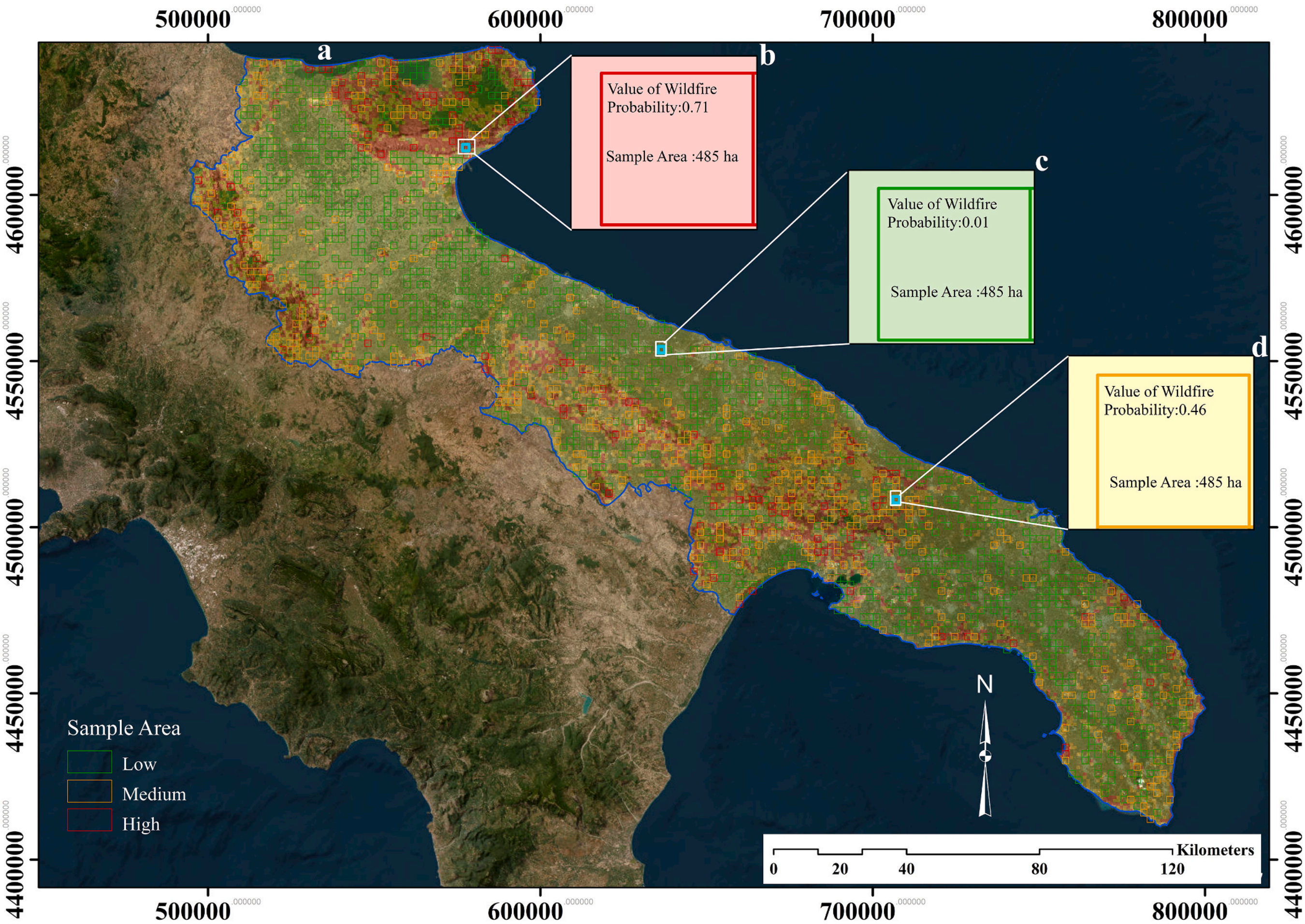

Fig. 4. (a) Location and distribution of sample areas; (b) applied samples in the High Wildfire Probability category; (c) applied samples in the Low Wildfire Probability category; and (c) applied samples in the Medium Wildfire Probability category. These sample areas ensure a balanced representation across different wildfire probability categories, facilitating a comprehensive analysis of road network connectivity and its influence on wildfire occurrence.

links was 0, indicating a lack of connectivity in those areas. On the contrary, the maximum value of 148 reflects instances of extensive connectivity; this finding indicates more developed infrastructure in certain regions. The Alpha values ranged from −0.33 to 0.92, denoting a significant variability in connectivity within the analyzed networks. A total of 66 values were zero or positive, implying that while some networks showed high connectivity, many were characterized by low or negative connectivity. The Beta values ranged from −0.22 to approximately 1.22, denoting considerable variability in the levels of connectivity and structure within the networks analyzed. A large number of values clustered between 0.5 and 1.0, demonstrating moderate to high levels of connectivity in many samples. The Gamma values ranged from 0 to 0.476, designating a moderate level of variability in whatever aspect of the system or structure they represented. A significant number of values were clustered around 0.25 to 0.35; this finding reveals that many instances or networks exhibited moderate levels of whatever aspect the metric Gamma represented (likely connectivity or efficiency). The Cyclomatic Number results showed that notable values were clustered between −5 and −15, designating lower complexity across multiple road networks. Zero values indicated a neutral state or minimal complexity. Zeroes might represent structures with little to no branching or decision points, signifying simplicity. The majority of Eta values ranged between 0.00 and 2.89, implying low to moderate complexity within the networks.

Road density values across various sample areas ranging from 8.9 m. ha^{-1} to 73.71 m.ha^{-1} are presented in Table 4. The majority of the values are concentrated between 15 m.ha^{-1} and 60 m.ha^{-1}. Overall, this indicates significant variability in road density among the sample areas, with several areas exhibiting relatively high density. The data provided display the number of nodes across various sample areas, with values ranging from 8 to 182. Most areas feature node counts between 30 and 100, indicating a moderate to high level of connectivity within these networks. The highest number of nodes recorded is 182, while the lowest is 8, these results demonstrate variation in the number of nodes among the sample areas. The dataset outlines the link counts across different sample areas, showing a wide range from 4 to 156. The majority of sample areas showed link counts falling between 20 and 100. The highest recorded link count is 156, while the minimum stands at 4. The Alpha values ranged from −0.33 to 0.02, indicating varying levels of connectivity within the network. Most of the values were negative, implying low to moderate connectivity across the sample areas, with most of the values clustering around −0.1 to −0.19. This variability highlights the differences in network structure and connectivity efficiency across the sample areas. The Beta values ranged from 0.4 to 1.0, indicating varying levels of connectivity efficiency across the sample areas. The majority of values were clustered between 0.62 and 0.94 (Table 3). Notably, several sample areas achieved the maximum value of 1.0, reflecting optimal connectivity. Conversely, the minimum value of 0.4 indicates a lower level of connectivity in certain areas. The Gamma values ranged from 0.146 to 0.362, reflecting a variety of connectivity levels among the sample areas. Most values clustered between 0.25 and 0.33. Some areas registered higher values, peaking at 0.362, thus indicating enhanced connectivity efficiency. Most of the Cyclomatic Number values were negative and clustered around −5 to −10, indicating low

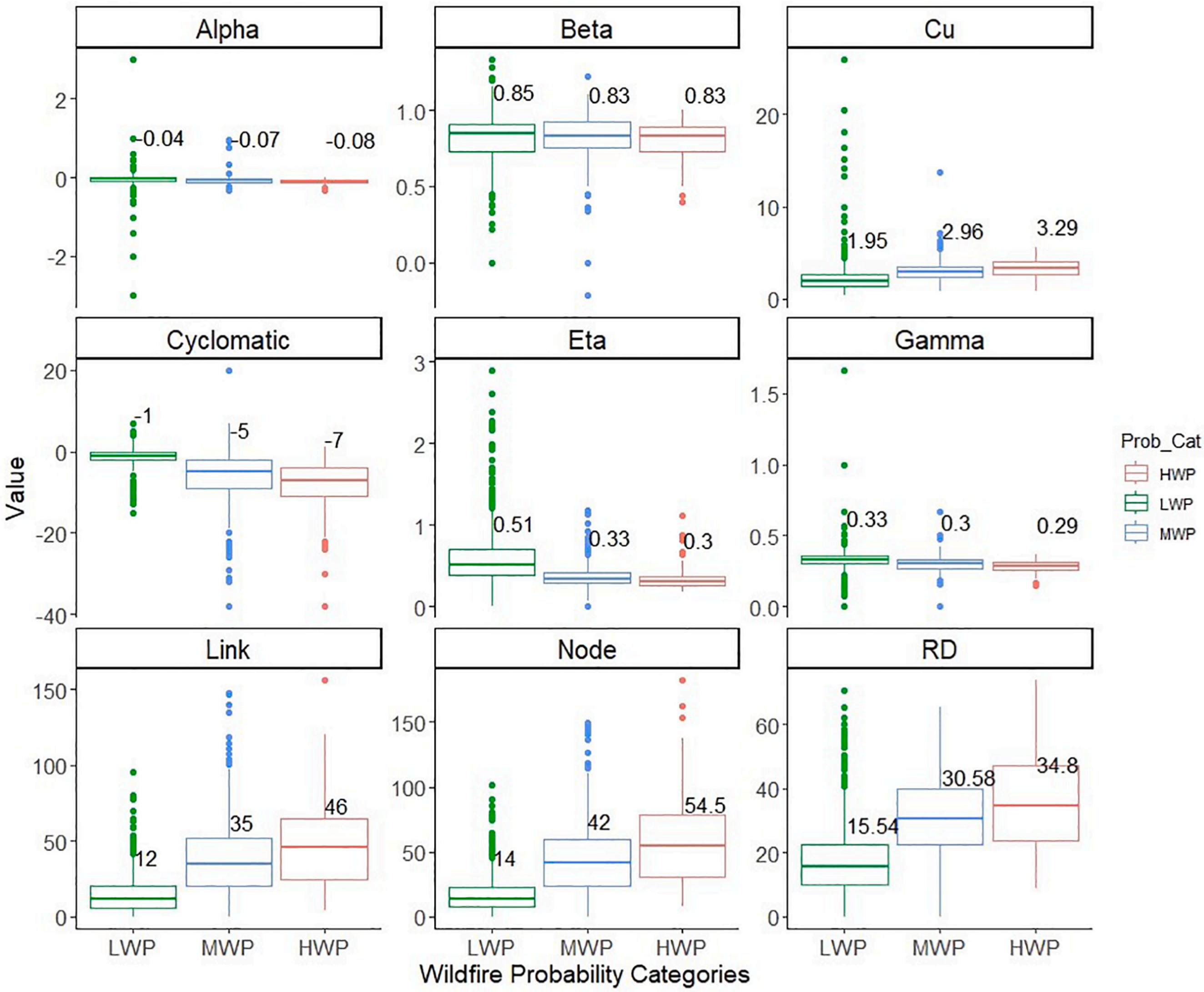

Fig. 5. This figure presents the distribution of key road network connectivity indices (Alpha, Beta, Cyclomatic, Eta, Gamma, Link, Node, and Road Density) across the three wildfire probability categories.

Table 2
Values of wildfire probability, road density, node count, link count, Alpha, Beta, Gamma, Eta and Cyclomatic Number for the Low Wildfire Probability category in the first three and last three sample areas..

Sample Area	Value of wildfire probability	Road Density (m.ha^{-1})	Node	Link	Alpha	Beta	Gamma	Eta	Cyclomatic Number
SA1	0.27	54.2	78	64	−0.09	0.82	0.28	0.32	−13
SA2	0.16	19.32	22	15	−0.15	0.68	0.23	0.49	−6
SA3	0.29	25.32	25	15	−0.20	0.6	0.21	0.64	−9
…	…	…	…	…	…	…	…	…	…
SA1014	0.03	37.62	48	38	−0.09	0.79	0.27	0.38	−9
SA1015	0.32	46.44	91	78	−0.07	0.86	0.29	0.22	−12
SA1016	0.03	53.10	102	96	−0.03	0.94	0.32	0.21	−5

complexity and limited connectivity in most regions. However, some areas showed slightly enhanced connectivity with values of zero or higher. This variation highlights the differences in network complexity and overall connectivity efficiency across the sampled areas. The Eta values ranged from 0 to 1.18, with the majority being between 0.7 and 0.9, indicating a notable variability in network efficiency across the analyzed areas.

The Kruskal-Wallis test results are shown in Table 5, where the test statistic (Chi-Squared), degrees of freedom (DF), and significance level (P-Value) are presented. Road Density, Node, Link, Alpha, Gamma, Cyclomatic Number, and Eta Index all exhibit highly significant differences among wildfire probability categories. A very high Chi-Squared value, along with an extremely small P-value, was obtained for Node, Link, and Road Density, respectively. The *p*-value for the Beta index is higher than 0.05, indicating no statistically significant difference among the categories.

The pair-wise comparisons between each of the Wildfire Probability Categories for each index using the post-hoc Dunn's test are shown in

Table 3
Values of wildfire probability, road density, node count, link count, Alpha, Beta, Gamma, Eta and Cyclomatic Number for the Medium Wildfire Probability category in the first three and last three sample areas.

Sample Area	Value of wildfire probability	Road Density m.ha^{-1}	Node	Link	Alpha	Beta	Gamma	Eta	Cyclomatic Number
SA1	0.63	63.99	147	114	−0.11	0.78	0.26	0.21	−32
SA2	0.48	51.32	78	64	−0.9	0.82	0.28	0.30	−13
SA3	0.43	30.45	32	20	−0.19	0.62	0.22	0.58	−11
…	…	…	…	…	…	…	…	…	…
SA379	0.40	59.46	144	119	−0.08	0.83	0.28	0.19	−24
SA380	0.48	64.15	143	148	0.02	1.03	0.35	0.16	6
SA381	0.47	30.82	72	68	−0.02	0.94	0.32	0.17	−3

Table 4
Values of wildfire probability, road density, node count, link count, Alpha, Beta, Gamma, Eta and Cyclomatic Numberfor the High Wildfire Probability category in the first three and last three sample areas.

Sample Area	Value of wildfire probability	Road Density m.ha^{-1}	Node	Link	Alpha	Beta	Gamma	Eta	Cyclomatic Number
SA1	0.91	55.20	116	79	−0.14	0.72	0.24	0.26	−30
SA2	0.91	57.31	87	80	−0.4	0.92	0.31	0.27	−6
SA3	0.70	39.31	67	53	−0.10	0.79	0.27	0.28	−13
…	…	…	…	…	…	…	…	…	…
SA122	0.74	41.61	69	58	−0.08	0.84	0.29	0.27	−10
SA123	0.81	43.83	96	88	−0.04	0.92	0.31	0.19	−7
SA124	0.82	31.99	63	61	−0.01	0.97	0.33	0.2	−1

Table 5
Kruskal-Wallis Test for road network connectivity indices among Wildfire Probability Categories.

Indices	Chi_Squared	DF	p_Value
Road Density	405.14	2.00	0.00*
Node	541.60	2.00	0.00*
Link	467.66	2.00	0.00*
Alpha	45.63	2.00	0.00*
Beta	1.184	2.00	0.55
Gamma	176.59	2.00	0.00*
Cyclomatic Number	353.07	2.00	0.00*
Eta	289.06	2.00	0.00*

* Significance at $p < 0.05$.

Table 6.. Significant differences were observed between LWP and HWP and LWP and MWP for all indices except for Eta and Beta. In contrast, significant differences between MWP and HWP were found only for the Node and Cyclomatic Number index. Notably, the Beta Index showed no significant differences across wildfire probability categories.

4. Discussion and conclusion

4.1. Wildfire probability and sample size allocation

Our study highlighted the relationship between specific connectivity indices of road networks and wildfire probability. To achieve these results, we employed an Artificial Neural Network (ANN) model to estimate wildfire probability in the Apulia region, incorporating multiple influential variables. Consistent with previous research (Syphard et al., 2008; Oliveira et al., 2012; Elia et al., 2020; Vilar et al., 2019), our model demonstrated high predictive accuracy, crucial for forecasting wildfire occurrence under varied environmental conditions. Evaluation metrics, such as RMSE for the validation dataset and AUC, confirmed the model's reliable performance.

The classification of wildfire probability into three categories low (LWP), moderate (MWP), and high (HWP) enabled clear spatial differentiation, assisting stakeholders in prioritizing monitoring efforts and resource allocation (Elia et al., 2015; Cabrera et al., 2024; Vigna et al., 2024). Approximately 66 % of the study area fell within the LWP category, likely due to favorable vegetation, moisture conditions, and limited anthropogenic pressure. Conversely, areas identified with elevated wildfire probability require focused management strategies to mitigate potential impacts. These high-risk zones are likely shaped by both biophysical and anthropogenic factors, including road proximity, vegetation density, and climate variability (Aparício et al., 2022; Chuvieco et al., 2023; Ochoa et al., 2024). While certain regions exhibit high

Table 6
Dunn- Bonferroni post -hoc.

Indices	Comparison wildfire probability categories	p-value
Road Density	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.15
Node	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.01*
Link	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.04
Alpha	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.04
Beta	LWP- HWP	0.87
	LWP – MWP	0.60
	MWP- HWP	0.48
Gamma	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.05
Cyclomatic Number	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.00*
Eta	LWP- HWP	0.00*
	LWP – MWP	0.00*
	MWP- HWP	0.06

* Significance at $p < 0.05$.

wildfire probability, not all areas are equally prone. The tripartite classification provides a refined understanding of fire risk, ensuring low-probability areas are distinguished from higher-risk ones. Though our ANN model achieved robust accuracy, we acknowledge possible overestimations in some zones due to model generalization. Nonetheless, the combined use of RMSE and AUC strengthens the model's alignment with observed patterns, reducing bias.

Sample allocation across wildfire categories for the analysis of road network connectivity indices was based on the Neyman allocation method, ensuring representative sampling. The LWP category received the majority of samples (66 %), reflecting its extensive coverage. MWP (21 %) and HWP (13 %) categories were proportionally represented, enhancing insight into areas of critical concern. Although HWP had fewer samples, allocation accuracy remained high (Wright, 2020), supporting targeted mitigation strategies (Pandey et al., 2023; Thi Hang et al., 2024). Detailed data from HWP areas can inform strategic planning, resource deployment, and the development of early warning systems.

4.2. Road network and connectivity indices

Statistical tests, including the Kruskal-Wallis test, revealed significant differences in connectivity indices across wildfire probability categories. These results underscore the inadequacy of a single uniform approach to road and fire management across heterogeneous landscapes. Instead, differentiated strategies based on specific road network characteristics are essential.

The Alpha index, which measures circuit connectivity, remained generally low across all wildfire probability categories, suggesting limited redundancy in the overall road network. However, post-hoc tests showed significantly higher Alpha values in HWP areas ($p \leq 0.04$), indicating slightly better loop connectivity in these zones (Sreelekha et al., 2016). Although improved circuit connectivity could enhance emergency responses (Freiria et al., 2015; Lai et al., 2024; Arango et al., 2024), the values still indicate limited redundancy. Contrary to expectations, the Beta index did not mirror the Alpha trend. With no significant differences among categories ($p = 0.55$), it suggests that while HWP areas may contain more loops, they lack superior link-to-node connectivity. This implies that improved loop connectivity does not necessarily translate into greater network flexibility.

A consistent increase in nodes, links, and road density from LWP to HWP indicates a strong association between dense, complex road networks and high wildfire probability. This supports previous findings that link road networks with anthropogenic ignition sources (Latham et al., 2009; Narayanaraj and Wimberly, 2012; Mostafa et al., 2017; Zambon et al., 2019; Mostafa et al., 2024). Statistically significant differences in these indices ($p = 0.00$) were confirmed via Kruskal-Wallis and Dunn-Bonferroni tests, with HWP areas showing the highest values. These patterns suggest that increased human access and land use changes contribute to higher fire risk. Accordingly, road network connectivity and accessibility are highest in HWP areas, making them more susceptible to wildfire ignition (Romero-Calcerrada et al., 2008; Vega Orozco et al., 2012; Ricotta et al., 2018, 2018).

To mitigate ignition probability, road links should be critically assessed based on their function and necessity. Redundant roads that contribute to increase ignition probability but do not support suppression efforts could be considered for removal (Beyki et al., 2023; Guerrero et al., 2023). Alternatively, roads essential for forestry or agriculture could be seasonally closed during peak fire periods, maintaining emergency access as needed. Where closures are not feasible, ignition risk can be reduced through fuel management (e.g., silviculture, firebreaks) (Guerrero et al., 2023; Marziliano et al., 2024) and by equipping areas with resources for fire response (e.g., water sources, evacuation routes) (Akhyar et al., 2024; Arango et al., 2024). In high-sensitivity HWP areas, especially those with critical infrastructure or ecological value, smart road technologies could provide early detection and rapid response capabilities (D'Este et al., 2021). These systems, equipped with sensors and real-time monitoring, enhance situational awareness and coordination for emergency responders (Rezaeifam et al., 2022; Akhyar et al., 2024).

The Cyclomatic Number showed a decreasing trend from LWP to HWP, reflecting lower network redundancy in high-risk areas. This may relate to more rugged terrain or dense vegetation (Liu and Zhao, 2015; Sarkar et al., 2020). Kruskal-Wallis tests confirmed significant differences ($\chi^2 = 353.07$, $p = 0.00$), with HWP areas having the lowest values. Lower redundancy can hinder evacuation and suppression during wildfires. In such areas, blocked roads may facilitate fire spread and limit access, warranting aerial firefighting support and designated helicopter landing zones (Bookbinder and Martell, 1979; Skorin-Kapov et al., 2024).

The Eta index, which reflects network efficiency, also decreased from LWP to HWP, indicating shorter average link lengths due to increased node density. While this may improve local access, it can reduce overall travel efficiency and complicate emergency logistics. Statistical analysis confirmed significant differences across categories ($\chi^2 = 289.06$, $p = 0.00$). Longer response times and limited routing options in HWP areas create bottlenecks during emergencies (Wu et al., 2020; Elassy et al., 2024) Enhancing efficiency through improved road planning and maintenance could support faster response and evacuation (Arango et al., 2024; Giannakidou et al., 2024; Kalogiannidis et al., 2024).

MWP areas displayed intermediate characteristics in connectivity and wildfire risk, suggesting a transitional role. Gaps in the network, highlighted by node and link counts, require strategic improvements. Planners should consider traffic patterns, peak usage (e.g., tourism), and road conditions (e.g., width, shoulders) to support emergency response (Bao et al., 2022; Cao et al., 2024; Marziliano et al., 2024; Necula, 2015). Future development should also incorporate urban expansion and climate change scenarios to enhance MWP resilience (Dey et al., 2023; Kim et al., 2023; Kumar et al., 2023).

4.3. Practical implications for policy and wildfire management

The insights gained from this study offer clear, actionable implications for policymakers, emergency planners, and transportation agencies. Effective wildfire management requires a differentiated approach based on wildfire probability zones, particularly focusing on high wildfire probability areas. In HWP zones, resource allocation should prioritize the establishment of firefighting stations, strategic water reservoirs, and smart fire detection systems. Concurrently, enhancing road network efficiency in low wildfire probability (LWP) areas is essential to ensure timely response and access during wildfire events. Prevention strategies in HWP areas should include roadside fuel management to reduce ignition risks, as well as the temporary restriction of access to high-risk roads during peak fire seasons. Emergency response planning must incorporate the development of alternative evacuation routes and investment in aerial rescue infrastructure for inaccessible or rugged terrain.

Long-term sustainable planning should aim to design multifunctional road networks that balance fire prevention with essential mobility needs. Integrating climate-resilient infrastructure capable of withstanding future wildfire conditions is crucial. Moreover, adaptive strategies should be embraced to replace rigid, outdated systems, especially when extreme events such as wildfires or hurricanes challenge existing planning paradigms. These "self-sealing" policy loops, where current road and wildfire strategies reinforce one another, can become self-correcting under such stressors, encouraging necessary revisions to infrastructure and emergency protocols (Moraci et al., 2020; Zurlini et al., 2014). By implementing these evidence-based recommendations, stakeholders can optimize road network design, enhance wildfire preparedness and response, and ultimately strengthen landscape resilience to wildfires.

5. Conclusion

This study underscores the significant relationship between road network characteristics and wildfire probability, emphasizing the importance of tailored management strategies aligned with spatial wildfire probability categories. By applying an Artificial Neural Network (ANN) model, we estimated wildfire probabilities using a comprehensive set of biophysical and anthropogenic variables. The results reveal that medium and high wildfire probability (MWP and HWP) areas exhibit distinct road network configurations that warrant specific interventions.

In HWP zones, effective mitigation strategies include selective road closures, roadside fuel management, and the deployment of smart road technologies such as real-time monitoring and early detection systems. MWP areas require improvements in traffic flow, road design, and emergency accessibility, particularly during peak congestion periods. Meanwhile, LWP areas, although less prone to fire, benefit from enhancements in road efficiency to ensure rapid emergency response when needed.

Our findings advocate differentiated, context-specific approaches to wildfire and infrastructure management. However, limitations such as potential dataset biases, particularly the underrepresentation of certain road types (e.g., rural or unpaved roads)—may influence the generalizability of the results. Future planning efforts should account for regional variability in road network structures to improve fire risk assessments and adaptive management practices.

While the findings from the Apulia region offer valuable insights, the principal contribution of this study lies in the development of a transferable methodological framework. By integrating wildfire probability mapping with detailed road network analysis, we provide a scalable, data-driven approach that can be applied to other regions facing wildfire risk. This framework enables the systematic identification of road infrastructure characteristics that influence fire dynamics and supports more informed, resilient planning for wildfire prevention, suppression, and post-fire recovery—well beyond the scope of the present case study.

CRediT authorship contribution statement

Mohsen Mostafa: Writing – original draft, Visualization, Validation, Methodology, Formal analysis. **Mario Elia:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization. **Vincenzo Giannico:** Writing – review & editing. **Fantina Tedim:** Writing – review & editing. **Giovanni Sanesi:** Writing – review & editing, Supervision. **Raffaele Lafortezza:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2025.114001.

Data availability

Data will be made available on request.

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