Ortega *et al. Fire Ecology* (2024) 20:40
https://doi.org/10.1186/s42408-024-00270-2

Fire Ecology

ORIGINAL RESEARCH

Open Access

Modeling fuel break effectiveness in southern Spain wildfires

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Abstract

Background Fuel breaks aim to reduce the energetic progression of a wildfire, facilitating safe and efficient suppression. Changes in fire regimes are creating increasingly complex scenarios in which a higher percentage of wildfires exceed control capabilities, and a significant increase in firefighting costs is expected. Therefore, it is necessary to redefine fuel break networks incorporating science-based criteria. This change entails the improvement of the existing fuel breaks, the abandonment of those whose effectiveness does not justify the investment in their maintenance, and the development of new optimized designs. Fuel break effectiveness is understood as the probability of controlling a fire in the treated area. We analyzed 563 intersections between fires and fuel breaks that occurred during wildfires from 2011 to 2018 considering topographic, meteorological, fuel, design feature, suppression, and fire behavior factors. The main goal of this study is to quantitatively analyze the effectiveness of fuel breaks during wildfires in southern Spain and to develop models to predict potential fuel break effectiveness in fire containment capabilities by comparing machine learning techniques with a classic statistical approach.

Results Fuel breaks were effective in containing the fire in 46.9% of cases. The most influential factors in effectiveness were the type of suppression work executed on fuel breaks (aerial, ground, or combined firefighting), the flame length, and the intersection angle between the fire and fuel break. Although the most accurate results were achieved with an artificial neural network, a decision tree could be the easiest model for end-user operational application.

Conclusions This study entails a change in effectiveness assessment to an empirical approach in real wildfires in Spain. Our findings can be used to support decision-making for optimizing fire containment capability and firefighter safety.

Keywords Preparedness, Firebreak, Fire containment capability, Suppression success, Firefighter safety, Quantitative analysis, Artificial neural network, Decision tree, Logistic regression

Resumen

Antecedentes El objetivo de los cortafuegos es la reducción de la progresión energética de los incendios forestales, facilitando trabajos de extinción seguros y eficientes. Los cambios en los regímenes de incendios están creando escenarios cada vez más complejos en los que un mayor porcentaje de incendios forestales superan la capacidad de extinción, esperándose un aumento significativo en los gastos de extinción. Por lo tanto, es necesario redefinir las redes de cortafuegos incorporando criterios basados en la ciencia. Este cambio implica la mejora de los cortafuegos existentes, el abandono de aquellos cuya efectividad no justifique la inversión en su mantenimiento, y el desarrollo de nuevos diseños optimizados. La efectividad de los cortafuegos se entiende como la probabilidad de control de

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un incendio forestal en el área tratada. Analizamos 563 intersecciones entre frentes de fuego y cortafuegos que ocurrieron durante incendios forestales entre 2011 y 2018, considerando factores topográficos, meteorológicos, de combustible, características de diseño, trabajos de extinción y comportamiento del fuego. El objetivo principal de este estudio es analizar cuantitativamente la efectividad de los cortafuegos durante incendios forestales en el sur de España y desarrollar modelos para predecir la efectividad potencial de los cortafuegos en las capacidades de contención del fuego mediante la comparación entre técnicas de aprendizaje automático y un enfoque estadístico clásico.

Resultados Los cortafuegos fueron efectivos en contener el fuego en el 46.9% de los casos. Los factores más influyentes en la efectividad fueron el tipo de trabajo de extinción ejecutado en los cortafuegos (aéreo, terrestre o combinado), la longitud de la llama y el ángulo de intersección entre el fuego y el cortafuegos. Aunque los resultados más precisos se lograron con una red neuronal, el árbol de decisión podría ser el modelo más fácil para la aplicación operativa a nivel de usuario final.

Conclusiones Este estudio implica un cambio en la evaluación de la efectividad de los cortafuegos hacia una aproximación empírica en incendios forestales reales en España. Nuestros resultados pueden usarse para apoyar el proceso de toma de decisiones, optimizando la capacidad de control del fuego y la seguridad de los combatientes.

Introduction

Wildfires can impact both society and the environment (Chung 2015; Plucinski 2019b), and fire agencies invest large amounts of resources to minimize their negative consequences in fire-prone regions (Penman et al. 2013; Katuwal et al. 2016; Alcasena et al. 2019). Traditionally, the implementation of suppression policies requires higher budgets than preparedness (Rigolot et al. 2009; Hand et al. 2014; Fernandes et al. 2016). Data demonstrate that suppression and preparedness have been effective at reducing the number of large fires (Fernandes et al. 2016). In Spain, a decrease in the average forest area affected by wildfires and in the percentage of large fires (> 500 ha) has been observed in recent decades (Cardil and Molina 2013). Despite the efforts made by fire agencies, wildfire management has become more complex due to global change. Several studies have shown that the fire hazard has increased in Mediterranean areas (Moreira et al. 2011) and that fire regimes have changed in size, intensity, severity, and frequency (Plucinski 2019b). Although increased suppression resources and the professionalization of fire agencies afford rising operational capability to fight and control wildfires (Castellnou et al. 2019), extreme wildfire events can exceed suppression capabilities (Rytwinski and Crowe 2010; Werth et al. 2016). In this global change scenario, preparedness plays an essential role in forest protection (Syphard et al. 2011b), reducing the negative impacts of wildfires.

Fuel breaks are defined as areas where the structure of the vegetation has been modified by reducing fuel load (breaking the horizontal and vertical continuity) or areas where the species composition has been manipulated to reduce flammability (Agee et al. 2000; Dupuy and Morvan 2005; Moreira et al. 2011). Traditionally, firebreaks are the most commonly used fuel breaks by fire agencies. Firebreaks were defined by Green (1977) as lines where all vegetation is removed down to mineral soil. Firebreaks have been found to be ineffective in certain scenarios and are being replaced by fuel reduction treatments conducted at larger scales (Kaiss et al. 2007; Penman et al. 2013).

Fuel breaks alter fire behavior and are designed to limit wildfire spread (Gannon et al. 2023; Young et al. 2023) and reduce burned area size (Finney et al. 2005; Duguy et al. 2007; Penman et al. 2013). When fuel breaks are implemented, they usually become essential factors in an integrated suppression strategy and prescribed burning plans, improving fire suppression response (Hand et al. 2014; Quilez et al. 2020) since they can serve as anchor points for direct or indirect attack. Therefore, fuel breaks typically increase suppression resource efficiency (Dupuy and Morvan 2005; Moreira et al. 2011; Syphard et al. 2011a; Kennedy and Johnson 2014; Rodríguez y Silva et al. 2020), improving fire line production rates (Katuwal et al. 2016; Ortega et al. 2023) and firefighter safety by providing safety zones, escape routes, and strategic zones where radiant heat reduction makes firefighter work possible (Martinson and Omi 2003; Penman et al. 2013; Katuwal et al. 2016; Plucinski 2019a, 2019b; Quílez et al. 2020).

According to Moreira et al. (2011), fuel break effectiveness is defined as the probability of controlling a fire (likelihood of control). Previous research demonstrated how fuel breaks were successfully used in stopping wildfires in different scenarios (Grenn 1977; Agee et al. 2000). However, other studies have also shown their ineffectiveness, especially under extreme weather conditions, large fire fronts or convective and downburst phenomena (Weatherspoon and Skinner 1996; Agee et al. 2000; Duguy et al. 2007; Moreira et al. 2011; Syphard et al. 2011b). However, a well-designed fuel break is effective under the right conditions (Kennedy and Johnson 2014) and justifies the financial investment in execution and maintenance. Nevertheless, due to budgetary constraints, fuel breaks are sometimes designed inappropriately or are not maintained properly over time (Grenn 1977; Weatherspoon and Skinner 1996; Quílez et al. 2020).

There are different methodologies for fuel break effectiveness assessment (Omi and Martinson 2002). The most extensively used method is testing the effects of fuel breaks on potential fire behavior by comparing the results of fire propagation simulations under different scenarios (Van Wagtendonk 1996; Stephens 1998; Finney 2001; Brose and Wade 2002; Parisien et al. 2006; Duguy et al. 2007; Vaillant et al. 2009; Rytwinski and Crowe 2010; Chung 2015; Morvan 2015; Pacheco and Claro 2018; Aparício et al. 2022). Some empirical approaches have analyzed fuel break effects on burned areas (Lambert et al. 1999; Agee et al. 2000; Omi and Martinson 2002; Schoennagel et al. 2004; Finney et al. 2005; Raymond and Peterson 2005; Stephens and Moghaddas 2005; Prichard and Peterson 2010; Cui et al. 2019). Furthermore, high-intensity experimental fires have been used to test fuel breaks (Moreira et al. 2011; McCaw et al. 2012). Finally, there are few empirical studies assessing fuel break effectiveness during wildfires (Rigolot and Alexandrian 2006; Syphard et al. 2011a, 2011b; Gannon et al. 2023; Young et al. 2023), and none of them has been conducted in Spain. More empirical data are thus needed on fuel break effectiveness under real fire conditions (Raymond and Peterson 2005; Moreira et al. 2011; Kennedy and Johnson 2014; Plucinski 2019a).

The hypothesis of this study is that fuel break effectiveness depends on a broad set of factors, such as topographic, meteorological, fuel, design feature, suppression, and fire behavior variables. This research aims to quantitatively analyze the effectiveness of existing fuel breaks during wildfires in southern Spain and to develop a model to predict the potential effectiveness of fuel breaks in containing wildfires based on the above variables. The novelty of this study is the empirical approach to the fuel break effectiveness assessment in Spain, including logistic regression (LR), decision tree (DT), and artificial neural network (ANN) models. LR is a simple, linear, and interpretable model for binary classification. DT is highly interpretable, capturing non-linear relationships, while ANN are less interpretable and suited for complex predictions. These modeling techniques have been used before in the analysis of wildfires but poorly in the assessment of fuel break effectiveness. Multilayer perceptron (MLP) is the most widely used ANN to predict wildfire occurrence (De Souza et al. 2015; Sayad et al. 2019), model wildfire spread patterns (McCormick 2002), or assess wildfire hazard (Stankevich 2020). Chu et al. (2002) applied LR, and Jaafari et al. (2018) applied a decision tree (DT) to predict wildfires.

Methods

Study area

This study was carried out in forest areas, shrublands, and grasslands of Andalusia, the southernmost region of Spain, which extends over 87.591 km^2. Andalusia has a Mediterranean climate with wet and mild winters and hot and dry summers. Due to orographic variability, the climate experiences important local variations that cause high biodiversity.

Andalusia is traversed by the Guadalquivir River in its central part, around which agriculture and population settlements have developed. Forest areas are concentrated in the mountains of the north (Sierra Morena Range) and south (Baetic Range). The vegetation is sclerophyll adapted to the Mediterranean climate but also to fire and human pressures. The forested sites are dominated by *Pinus* (natural and artificial stands) and *Quercus* (cork and evergreen oak). Along river valleys, deciduous species, such as *Populus*, *Ulmus*, *Alnus*, and *Fraxinus* can be found. The understory is rich in species, such as *Quercus*, *Cistus*, *Cytisus*, *Genista*, *Erica*, *Juniperus*, *Salvia*, *Pistacia*, and *Phillyrea*. Shrublands usually cover the higher slope zones, whereas valleys and lower slope areas are dominated by dehesa systems (isolated *Quercus* trees with grassland for livestock production).

Andalusian landscapes are usually characterized by a fragmented distribution of remnant vegetation with high heterogeneity and complex mixed structures (Agee et al. 2000). These ecosystems are fire-prone areas in which fires have always been present. Wildfires and burnings for pasture production have traditionally modeled the landscape. Official regional statistics (Junta de Andalucía 2021) show a total of 645 outbreaks of fires (< 1 ha) and 1301 wildfires (> 1 ha) that burned 57,142.86 ha in Andalusia during the studied period (2011–2018). The fire regime in Andalusia is characterized by more than 80% of fire events burning an area smaller than 1 ha, while large wildfires (> 500 ha) typically account for over 50% of the total burned annual area. Moreover, the occurrence of wildfires exhibits a marked seasonality, focusing on the summer months (between June and August). Over 90% of wildfires in the region are caused by humans, with a minimum incidence of lightning in the historical dataset.

Data gathering

The Andalusian fire agency (INFOCA) compiles plentiful information about its firefighting work on wildfires. We used INFOCA's information gathered from wildfires that occurred from 2011 to 2018 to characterize and parameterize wildfire encounters with fuel breaks. Due to difficulties in compilation and the lack of accuracy of some variables, we supplemented the information with variables simulated with Visual Fuego (a free simulation software downloadable from www.labif.es; Rodríguez y Silva and Molina 2010) based on the BEHAVE and Albini models (Albini 1976; Andrews 2009). The non-geospatial generated database constitutes the data source for our study.

Variables related to topography, meteorology, fuel, fuel break design features, suppression, and fire behavior were identified as possibly influencing fuel break effectiveness (Table 1). These variables refer to the time at which the encounter between fire and fuel break occurred. Topographic data were obtained from a digital terrain model with a spatial resolution of 5 m. Meteorological information was generated from the Agroclimatic Information System for Irrigation (SIAR 2021) using an hourly register from the weather station closest to each wildfire. The fuel model was characterized based on the UCO 40 classification (Molina and Rodríguez y Silva 2012). Thirty-one fuel models were identified in the studied wildfires. To reduce the number of categories, they were regrouped into 12 groups depending on the potential fire behavior.

Following the methods described in Narayanaraj and Wimberly (2012), Hosseini et al. (2016), Katuwal et al. (2016), and Thompson et al. (2021), we considered all fire encounters with both fuel breaks and firebreaks that included vegetation-free strips, roads, paths, railroad tracks, water pipelines, irrigation channels, and rivers. Moreover, the spatial coupling of different linear fuel breaks was taken into account following Agee et al. (2000). The fuel break types were categorized into three groups based on the presence or absence of vegetation at the moment of the fire based on reported wildfire information. As a consequence, the maintenance condition was implicitly in this variable, as a lack of maintenance led to fuel break revegetation. The fuel break width was obtained from orthophotos. Fire behavior was classified into three types (surface, passive crown fire with individual tree torching, and active crown fire) according to real observations in the field during fire suppression. The rate of spread, flame length, and spotting distance were qualitatively captured by INFOCA observers in wide bins. Therefore, we also simulated these variables to obtain a more precise estimation of fire behavior. We removed the records that did not match the real observation thresholds. Campbell's alignment of forces (Campbell 2005) refers to the interaction of three key factors in wildfires: the slope of the terrain, the wind, and the exposure of the area to the sun (preheat). This combination can significantly increase the intensity of the fire behavior.

Exploratory analyses

Fuel break effectiveness is understood in this study as the probability of controlling a fire in the treated area. From the information gathered, effectiveness (EFFEC) was identified as the dependent variable, and 23 factors were recognized as independent variables. EFFEC is a qualitative dichotomous variable, and the independent variables are both categorical and continuous variables. Although models based on artificial intelligence do not require as many implementation considerations as the classic ones (Carvacho 1998), we conducted variable selection following Palmer et al. (2011). We discriminated variables by choosing those that most significantly affected the outcome. Variable selections are necessary to avoid irrelevant and correlated variables, reduce model complexity, and improve interpretability. Exploratory analyses were carried out prior to the construction of the predictive models. The SPSS© software was used for all statistical data analyses. The procedure followed in this study to assess the normality of quantitative variables was the Kolmogorov–Smirnov test ($p > 0.05$). We used Spearman's rank correlation coefficient to identify linear correlation ($p < 0.05$) between quantitative variables without a normal distribution, and the chi-squared test (χ^2) was performed to find associations ($p < 0.05$) between qualitative variables and multinomial distributions. Cramer's V was used as a measure of association between qualitative variables. In addition, a two-step cluster analysis was performed as a useful exploratory technique for clustering the combination of quantitative and qualitative variables. The number of clusters was automatically calculated based on the log-likelihood distance measure and the Bayesian Information Criterion (BIC).

Effectiveness models

The SPSS© software was used to model the fuel break effectiveness. Modeling was conducted based on the principle of parsimony, analyzing both linear and non-linear effects and maximizing model interpretability and predictive accuracy. Once the group of variables was selected, the effectiveness was modeled using logistic regression, a classic statistical method, and two machine learning methods to consider non-linear effects while enhancing model interpretability (DT) and predictive accuracy (ANN). According to Palmer et al. (2011), the models were trained with all variables and retrained by removing variables one by one until there was a noticeable decrease in model performance (backward elimination). Predictive model performances were calculated on validation samples for the purpose of obtaining more realistic estimations. The internal validation methods employed were bootstrapping resampling for LR,

Table 1 Description of the studied variables

Variables	Source	Range	Type	Units or categories
Topographic variables				
Slope	INFOCA	0–65	Q*n*	%
Aspect	INFOCA	1–2	Ql	1 (sunshine) 2 (shade)
Meteorological variables				
Temperature	SIAR 2021	4.85–43.47	Q*n*	°C
Relative humidity	SIAR 2021	6.14–85	Q*n*	%
Wind speed (*U*)	SIAR 2021	0–32	Q*n*	km/h
Fuel variables				
Fine fuel moisture content (FFMC) (Rothermel 1983)	Own data	6.25–13.63	Q*n*	%
Fuel model (UCO 40) (FM) (Molina and Rodríguez y Silva 2012)	Own data from INFOCA report (conversion of Rothermel classification to UCO 40)	1–12	Ql	1 (grass in semiarid conditions; P1, P2. P3, P4, P7) 2 (grass in subhumid conditions; P5, P6, P8) 3 (mixture of grass and shrubs lower than 60 cm high; PM1, PM3) 4 (mixture of grass and shrub higher than 60 cm high; PM2, PM4) 5 (shrub lower than 0.5 m high; M1, M2) 6 (shrub approximately 1 m in height; M3, M4, M6) 7 (chaparral shrub; M5, M7, M8, M9) 8 (grass, shrub, or litter lower than 30 cm in height or depth; HPM1, HPM2) 9 (grass, shrub, or litter between 30 and 90 cm in height or depth; HPM3, HPM4) 10 (grass, shrub, or litter more than 90 cm in height or depth; HPM5) 11 (slash and pine litter; HR5, HR7) 12 (slash and broadleaf litter; HR6, HR9, R1)
Fuel break design features				
Fuel break type (PIT)	INFOCA	1–3	Ql	1 (vegetation-free: firebreak) 2 (combination of vegetation-free and vegetated: firebreak with adjacent vegetation-treated area) 3 (vegetated: vegetation treated area)
Fuel break location (LOC)	Own data	1–6	Ql	1 (steepest slope) 2 (flat) 3 (ridgeline) 4 (lower slope) 5 (mid-slope) 6 (canyon bottom)
Fuel break width (*W*)	Own data	1.5–450	Q*n*	m
Suppression variables				
Type of suppression work executed on fuel break (SW)	INFOCA	1–5	Ql	1 (combined ground-aerial firefighting) 2 (ground firefighting) 3 (aerial firefighting) 4 (fire spread with no suppression due to technical reasons) 5 (fire spread with no suppression due to safety reasons)
Firefighter safety	INFOCA	0–2	Ql	0 (non-safe) 1 (safe) 2 (unknown)
Fuel break effectiveness (EFFEC) representing if the fire spread was controlled in the fuel break	Own data	0–1	Ql	0 (non-effective) 1 (effective)

Table 1 (continued)

Variables	Source	Range	Type	Units or categories
Cause of fuel break leap	INFOCA	1–4	Ql	1 (no leap) 2 (radiation-convection) 3 (spotting) 4 (radiation-convection and spotting)
Observed fire characteristics				
Wildfire type (WT)	INFOCA	1–3	Ql	1 (surface fire) 2 (passive crown fire) 3 (active crown fire)
Burned area	INFOCA	0.02–9806	Q*n*	ha
Wildfire front length (*L*) representing the length of the portion of fire that encountered the fuel break	INFOCA	1–8	Ql	1 (< 50 m) 2 (50–100 m) 3 (100–250 m) 4 (250–400 m) 5 (400–600 m) 6 (600–800 m) 7 (800–1000 m) 8 (> 1000 m)
Alignment of forces (AF) (Campbell 2005) representing the arrangement of various factors that influence the behavior and spread of a wildfire (wind, slope, and preheat)	Own data	0–3	Ql	0 (0/3; out of alignment) 1 (1/3; half alignment: one factor) 2 (2/3; half alignment: two factors) 3 (3/3; full alignment: wind, slope, and preheat)
Propagation vector	INFOCA	1–4	Ql	1 (fuel) 2 (wind) 3 (topography) 4 (convective)
Intersection angle between fire and fuel break (encounter type) (ANG)	Own data	1–3	Ql	1 (almost parallel, flanking) 2 (lateral, flanking) 3 (perpendicular, heading)
Predicted fire behavior				
Rate of spread (ROS) (Andrews 2009)	Own data	0.1–263	Q*n*	m/min
Flame length (FL) (Byram 1959)	Own data	0.1–17.15	Q*n*	m
Spotting distance (Albini 1976)	Own data	0.8–288.35	Q*n*	m

Ql qualitative variable, *Qn* quantitative variable

cross-validation for DT, and split-sample validation for the ANN model.

Logistic regression (LR)

We modeled fuel break effectiveness with a binary logistic regression (Eq. 1), setting a cutoff value of 0.5. Wald significance tests were performed to evaluate the significance ($p < 0.05$) of the variables. Omnibus tests of model coefficients were used to check the model improvement over the baseline model. Nagelkerke's R-squared was utilized as a measure of the predictive power of the model. The Hosmer and Lemeshow test ($p > 0.05$) was conducted to determine the goodness-of-fit.

$$P\,(Y = 1|X) = \frac{1}{1 + e^{-(b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n)}} \tag{1}$$

where $P\,(Y{=}1 \mid X)$ is the probability that Y is 1, x_i are the independent variables, b_0 is the constant of the model, and b_i are independent variable constants.

Decision tree (DT)

DT is a non-supervised non-parametric learning method. Data are divided recurrently into subsets as states of the objective variable. Inputs are evaluated based on their impact on the predicted variable at each tree division, creating rules for predicting future events. The model was performed using an exhaustive CHAID tree-growing algorithm.

Artificial neural network (ANN)

ANN was performed with a multilayer perceptron function (MLP). An MLP is a supervised learning method with backpropagation as the training algorithm. A sigmoid type of hidden layer activation function and a softmax type of output layer activation function were chosen. Seventy percent of records were used to train the neural network and derive the model (training sample); 15% constituted the test sample, used to track errors during training; and 15% were used to assess the final neural network (reserved sample).

A receiver operating characteristic (ROC) curve was used to assess the performance of the model (Palmer et al. 2011; Jaafari et al. 2018; Gholamnia et al. 2020). The area under the ROC curve (AUC) is a measure of classification performance.

Results

Exploratory analyses

A total of 563 wildfire encounters with fuel breaks from 220 wildfires were recorded and characterized to model fuel break effectiveness. In 46.9% of cases, fuel breaks were effective in containing the fire. The percentage of fuel breaks that were effective by themselves, regardless of any suppression work, was 6.66%. However, fuel breaks supported by aerial firefighting had an increase in effectiveness to 15.9%. This increase was even greater (76.74%) when only ground firefighting was carried out. The highest degree of effectiveness (77.15%) was achieved with the combination of aerial and ground firefighting.

The first approach to variable selection led to discarding slope and exposure because of their implication in fire behavior variables. None of the quantitative variables showed a normal distribution. Spearman's rank correlation coefficient revealed linear relationships between some variables. FL and W make sense in modeling and are easily estimated for future predictions; therefore, we prioritized them over the rest of the quantitative variables, removing those that were correlated with them (ROS, U, and FFMC). Cramer's V showed an association between WT and FM. Consequently, a combination of both variables should be avoided. We selected FM and removed WT due to the ease of identification in the field. Therefore, the independent variables selected as inputs for subsequent modeling were fuel model (FM), fire front length (L), alignment of forces (AF), fuel break type (PIT), fuel break location (LOC), fuel break width (W), intersection angle between fire and fuel break (ANG), type of suppression work executed on fuel break (SW), and flame length (FL).

Two-step cluster analysis revealed patterns in the input dataset, resulting in two clusters: 46.9% of the sample corresponded to fuel breaks that effectively contained fires ("effective cluster"), and 53.1% corresponded to non-effective fuel breaks ("non-effective cluster"). The variables with the greatest normalized importance in determining these groups were EFFEC (100%), SW (48%), FL (27%), ANG (18%), AF (14%), and L (12%). Lesser normalized importance was shown by FM (4%), PIT (3%), LOC (3%), and W (1%). Figure 1 shows the variable contribution in percentage for each cluster based on the ranges (i.e., continuous variables) and categories (i.e., discrete variables) described in Table 1.

The cluster of "effective" fuel breaks was characterized by the following aspects: the type of suppression work executed on the fuel break was mainly combined ground-aerial firefighting and ground firefighting. The average flame length was 2.42 m. Almost parallel intersections predominated over the rest of the angles. The most representative alignment of forces was 0/3. The fire front length was usually under 400 m. The more representative fuel models were shrubs lower than 0.5 m in height and slash and pine litter. The characteristic fuel break of the "effective" cluster was firebreaks with adjacent vegetation-treated areas located in flats, ridgelines, and lower slopes. The average fuel break width was 17.30 m.

The cluster of "non-effective" fuel breaks was characterized by the following features: combined ground-aerial firefighting and ground firefighting did not support them. The average flame length was 4.41 m. Perpendicular intersections predominated over the rest of the angles. The most representative alignment of forces was 3/3, never occurring as 0/3 alignments. A fire front length of over 400 m stood out. The more representative fuel models were chaparral shrubs and grass, shrubs, or litter at heights or depths exceeding 90 cm. The characteristic fuel break of the "non-effective" cluster was vegetation-free, located at the mid-slope, steepest slope, and canyon bottom. The average fuel break width was 13.11 m.

Effectiveness models

Logistic regression (LR) model

The LR model results are shown in Table 2. FM was discarded due to the Wald test result ($p > 0.05$), which indicated that this variable did not explain effectiveness. AF, despite being significant, was also discarded because it has a standard error much greater than 1 and exp (b_1) = 0. Omnibus tests of model coefficients resulted in a highly significant chi-square ($p < 0.05$), so our new model was meaningfully better than the baseline model. Nagelkerke's R-squared suggested that the model was explanatory because it explained approximately 76% of the variation in the outcome. The Hosmer and Lemeshow test of goodness-of-fit suggested that the model was a good fit to the data.

Decision tree (DT) model

The independent variables selected by the DT modeling were type of suppression work executed on fuel break (SW), flame length (FL), fuel break width (W), intersection angle between fire and fuel break (ANG), and fuel break location (LOC). Fuel break effectiveness depended, first, on the type of suppression work providing support (Fig. 2). Fuel breaks where ground or combined ground-aerial firefighting provided support reached 77.1% effectiveness. However, this percentage

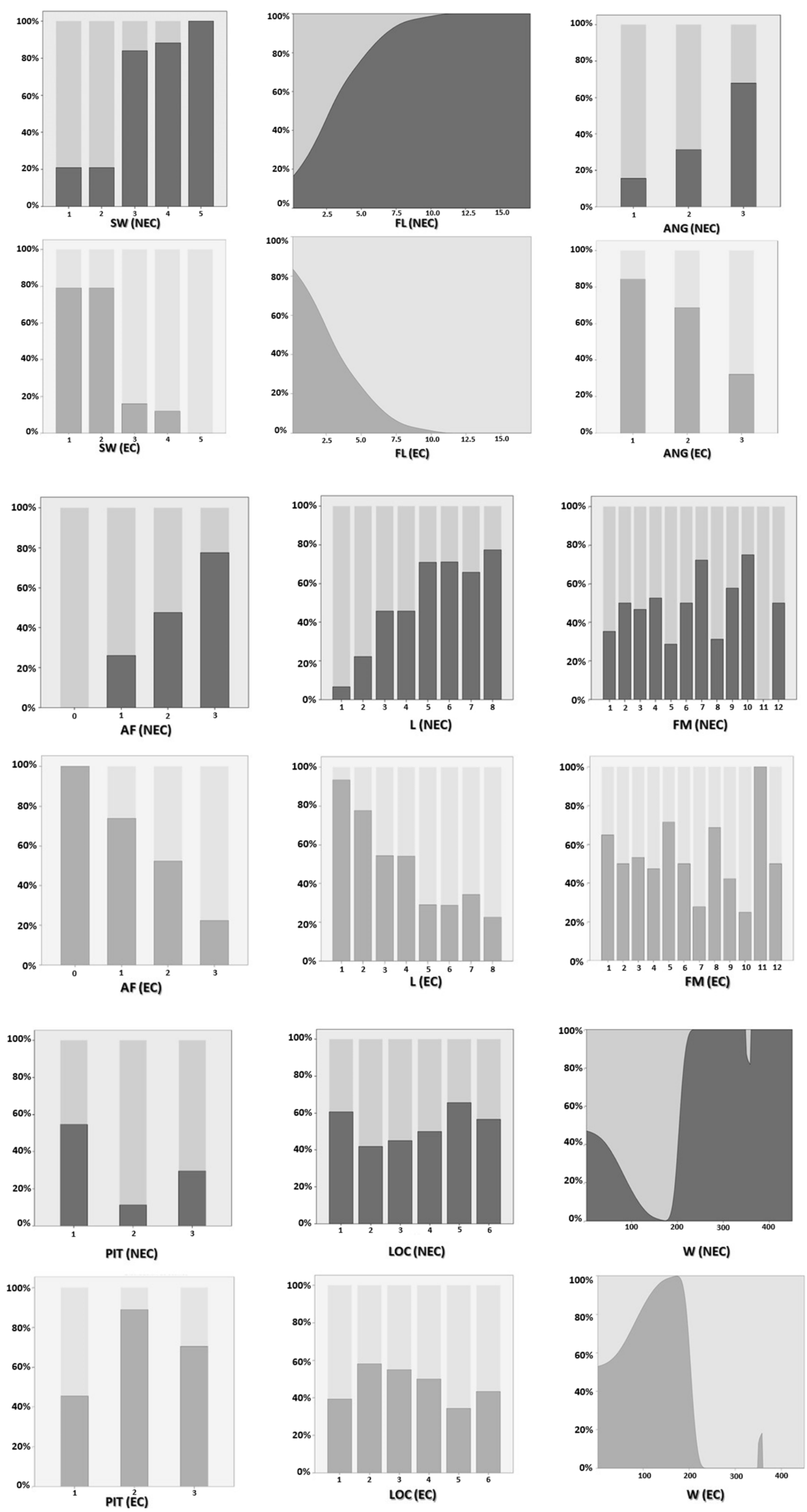

Fig. 1 Relative distributions of variables in each cluster. Dark gray in each chart represents non-effective cluster (NEC) and light gray represents effective cluster (EC). SW, type of suppression work executed on fuel break; FL, flame length; ANG, intersection angle between fire and fuel break; AF, alignment of forces based on Campbell's System; L, fire front length; FM, fuel model; PIT, fuel break type; LOC, fuel break location; W, fuel break width

Table 2 Variable equation table of the LR model

Variables	*B*	SE	Odds ratio Exp(*B*)
Fire front length (*L*)			
< 50 m	− 1,056	1,136	0,348
50–100 m	− 1,782	1,092	0,168
100–250 m	− 1,781	1,081	0,168
250–400 m	− 3,114	1,145	0,044
400–600 m	− 2,939	1,211	0,053
600–800 m	− 2,324	1,247	0,098
800–1000 m	− 3,385	1,179	0,034
> 1000 m			
Fuel break type (PIT)			
Vegetation-free	3,192	1,174	24,330
Combination of vegetation-free and vegetated	2,530	1,004	12,556
Vegetated			
Fuel break location (LOC)			
Steepest slope	0,887	0,721	2,429
Flat	1,411	0,718	4,101
Ridgeline	1,397	0,991	4,042
Lower slope	0,318	0,711	1,375
Mid-slope	1,320	0,919	3,745
Canyon bottom			
Fuel break width (*W*)	0,017	0,005	1,017
Intersection angle between fire and fuel break (ANG)			
Almost parallel	− 1,202	0,545	0,301
Lateral	− 2,127	0,504	0,119
Perpendicular			
Type of suppression work executed on fuel break (SW)			
Combined ground-aerial firefighting	0,292	0,523	1,339
Ground firefighting	− 2,305	0,404	0,100
Aerial firefighting	− 3,479	0,485	0,031
Fire spread with no suppression due to technical reasons	− 21,396	4201,908	0,000
Fire spread with no suppression due to safety reasons			
Flame length (FL)	− 0,536	0,104	0,585
Constant (b_0)	5,226	1,302	186,125

varied according to flame length. If the flame length was lower than 1.2 m, the effectiveness was 100%, regardless of the rest of the variables. The effectiveness remained very high (92.2%) for flame lengths between 1.2 and 3.3 m and widths greater than 6.5 m. If the width was less than 6.5 m, the effectiveness also depended on the intersection angle between the fire and fuel break (encounter type). On the one hand, when fire intersected fuel breaks almost in parallel, effectiveness remained very high (94.7%). On the other hand, when the intersection was lateral or perpendicular, the fuel break location played an important role in effectiveness. Ridgeline locations were more effective (89.5%) than the rest of the locations (46.3%).

When fire encountered fuel breaks and there was no suppression, the effectiveness was reduced to 9.9%. This value substantially increased (46.7%) when fire intersected fuel breaks almost in parallel. With lateral intersections, aerial firefighting increased effectiveness by 36% compared to free fire spread. In the case of perpendicular intersections, the fuel break effectiveness was very low (5.6%). However, this value increased to 16.5% in flat and lower slope locations.

Artificial neural network (ANN) model

The diagram of the selected MLP neural network was composed of an input layer whose predictors are fuel model (FM), fire front length (*L*), alignment of forces

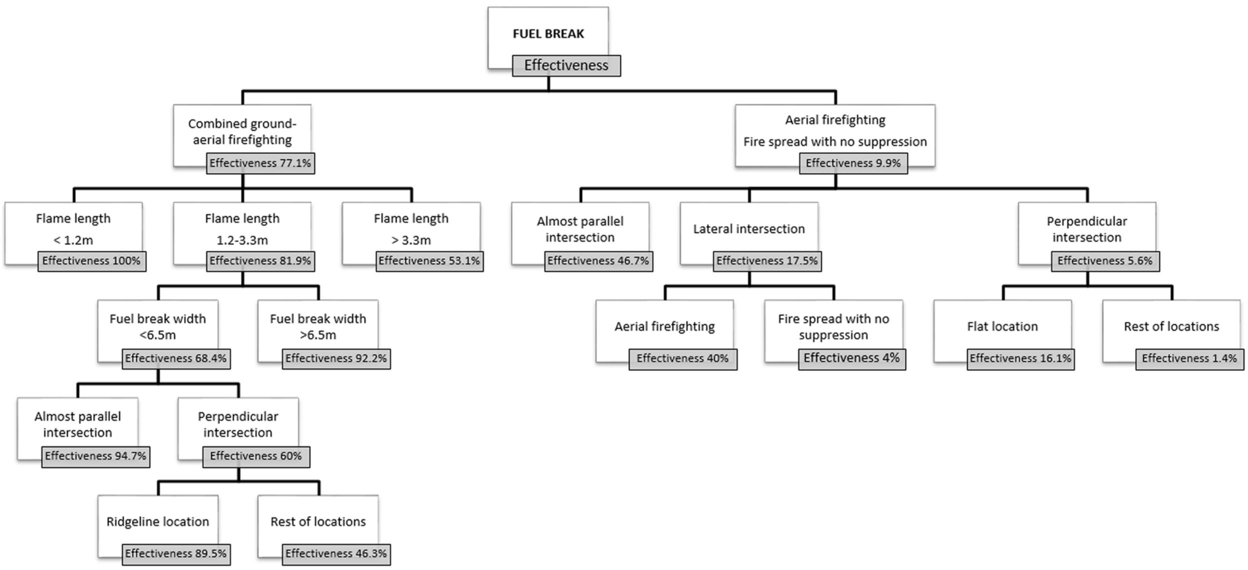

Fig. 2 Decision tree (DT) representation. EFFEC, effectiveness; SW, type of suppression work executed on fuel break; FL, flame length; ANG, intersection angle between fire and fuel break; W, fuel break width; LOC, fuel break location

Table 3 Comparison of the confusion matrix of validated models

Observed	Predicted percentage correct		
	LR	DT	ANN
Non-effective fuel break	86.3%	83.6%	90.9%
Effective fuel break	88.3%	83.3%	87.5%
Overall percentage	87.2%	83.5%	89.3%

LR logistic regression, *DT* decision tree, *ANN* artificial neural network

(AF), fuel break type (PIT), fuel break location (LOC), intersection angle between fire and fuel break (ANG), type of suppression work executed on fuel break (SW), fuel break width (*W*), and flame length (FL), a hidden layer with eight units and an output layer with two units (non-effective or effective) of the dependent variable (EFFEC). The normalized importance of the variables followed the order SW (100%), PIT (78.8%), *L* (61.7%), AF (52.3%), FL (44.2%), LOC (41.6%), ANG (37.9%), FM (36.3%), and *W* (17.6%). The model ensured a reliable classification ability because the AUC acquired a value of 0.94 in both categories of the dependent variable.

Comparison of model performance

The predictive model performances (Table 3) showed that the ANN had the highest accuracy, followed by LR and DT. The ANN model classified "non-effective" and "effective" correctly for 90.9% and 87.5% of the total number of estimates, respectively, with an overall percentage of 89.3%. The LR model classified "non-effective" correctly 86.3% and "effective" correctly for 88.3% of the total number of estimates, with an overall percentage of 87.2%. The overall percentage correctly classified by the DT model was 83.5%, with 83.6% for "non-effective" and 83.3% for "effective."

Discussion

In addition to the classical linear model, the statistical techniques used in this study, both in the exploratory analysis and in modeling, enabled us to work with a combination of quantitative and qualitative variables. These techniques also allowed us to process data that do not fulfill the classic applicability conditions, such as quantitative variables without normal distributions or variables with linear relationships with other study variables. These models are robust without having heavy data requirements (Carvacho 1998; McCormick 2002; Rubio-Hurtado and Vilá-Baños 2016). Evaluating the model performance results, artificial neural network, logistic regression, and decision tree all achieved great goodness-of-fit. Therefore, the possibility of predicting fuel break effectiveness was confirmed. The three models are accepted, and the independent variables considered are reliable predictors of the dependent variable. Artificial neural networks are recognized as the best method for modeling fuel break effectiveness (Table 3). In line with other studies, artificial neural networks offer predictions with good explanatory power (McCormick 2002) and have been shown to be highly effective as estimators (Carvacho 1998), with a high pattern recognition capability (Sáenz and Ballesteros 2002). Nevertheless, artificial neural network presents the greatest difficulty of interpretation and application (Palmer et al. 2011). In contrast, decision tree is the easiest model due to the simplicity of interpretation. Logistic regression presents an intermediate difficulty between the other two.

A total of 46.9% of the fuel breaks analyzed in southern Spain were effective in containing wildfires. These data are consistent with Syphard et al. (2011b), who showed that wildfires were stopped at fuel breaks 46% of the time in southern California (USA). The logistic regression model identified the type of suppression work executed on fuel break (SW), the flame length (FL), the intersection angle between fire and fuel break (ANG), and the fuel break width (*W*) as the variables with the greatest predictive significance. The decision tree model identified the type of suppression work executed on fuel break (SW), the flame length (FL), the fuel break width (*W*), and the intersection angle between fire and fuel break (ANG) as the variables with the highest predictive importance. Finally, the artificial neural network identified the type of suppression work executed on fuel break (SW), the fuel break type (PIT), the wildfire front length (*L*), and the alignment of forces (AF) as the most significant predictive variables. Therefore, the three predictive models performed with different techniques (logistic regression, decision tree, and artificial neural network), along with the two-step cluster exploratory analyses, identified the type of suppression work executed on fuel break (SW) as the variable with the most influence on fuel break effectiveness. Some studies (Agee et al. 2000; Syphard et al. 2011b; Katuwal et al. 2016; Gannon et al. 2023; Young et al. 2023) considered suppression as an important predictor of effectiveness as well. Our study confirmed that fuel breaks do not stop fires by themselves (6.66% effectiveness), which is consistent with the results of Agee et al. (2000). This means that without suppression resources, fuel breaks are unlikely to stop fire progression. The results of this research also indicated that flame length (FL), intersection angle between fire and fuel break (ANG), fuel break width (*W*), fuel break type (PIT), wildfire front length (*L*), and the alignment of forces (AF) are critical variables for successful wildfire control in fuel breaks. Regarding flame length (FL), intense fire behavior (higher flame lengths) significantly reduces fuel break effectiveness, in agreement with Agee et al. (2000), Katuwal et al. (2016), and Gannon et al. (2023). Regarding the intersection angle between fire and fuel break (ANG), fuel breaks have been shown to be more effective when intersections are almost parallel (flanking fire behavior). This variable has been scarcely considered prior to this study (Gannon et al. 2023; Young et al. 2023). The fact that fuel breaks work better when flame fronts reach them at an angle far from orthogonal, especially when wildfire front length (*L*) is low, means that they work better at containing flanks rather than head flame fronts. Regarding fuel break width (*W*), it has always been considered that the wider the widths, the greater the effectiveness (Agee et al. 2000; Cui et al. 2019), and the safer the firefighter work (Grenn 1977). The type of suppression work executed on fuel break (SW) is related to the fuel break width (*W*), as it enables the reduction of radiation heat from the fire front and enhances the performance of suppression efforts. The independent variable known as the fuel break type (PIT) is comparable to the fuel break maintenance conditions. According to the results, fuel break type (PIT) is a significant variable in effectiveness assessment, as also found in Syphard et al. (2011b), Hand et al. (2014), and Thompson et al. (2021). Contrary to the results obtained by Martinson and Omi (2003), many studies (Agee et al. 2000; Finney et al. 2005; Liu et al. 2013; Chung 2015) found that firebreaks should be periodically maintained to preserve their effectiveness. In regard to the alignment of forces (AF), no other previous studies have considered this predictive variable.

Previous research identified weather conditions (Schoennagel et al. 2004; Syphard et al. 2011b; Katuwal et al. 2016; Gannon et al. 2023), fuel characteristics (Grenn 1977; Agee et al. 2000; Schoennagel et al. 2004; Syphard et al. 2011b; Thompson et al. 2021), or topographic characteristics (Syphard et al. 2011b; Thompson et al. 2021; Gannon et al. 2023; Young et al. 2023) as significant variables explaining fuel break effectiveness. In our study, these variables were highly correlated with fire behavior characteristics and implicitly considered by our models. Agee et al. (2000) and Katuwal et al. (2016) also identified fire behavior as affecting fuel break effectiveness. In turn, Syphard et al. (2011b) identified the total fire size as an important predictor of effectiveness. In our study, the burned area at the moment of the encounters could not be included as an independent variable in the models because of the difficulty of knowing it accurately. Final burned area data were gathered for each wildfire; however, this variable is not significant in our study because it did not match the fire size at the time the fire front encountered the fuel break. Instead, fire front length (*L*) was evaluated and contributed to fuel break effectiveness.

It should be noted that the results are based on the acquisition of information from monitoring, expertise, and simulations, a hybrid model combining more than one data-mining technique, as proposed by Souza et al. (2015). Because wildfires are complex systems, wildfire records from the INFOCA database included imprecise and subjective data gathered by different observers with different criteria. However, the information collected made it possible to generate a wide non-geospatial database of intersections between fire fronts and fuel breaks that occurred during wildfires. The large number of records implies broad ranges of the studied variables, enabling extensive applicability of the study. The main constraints in our models include the low number of crown fire events and the limited range of wind speed compared to other variables.

Our results have a dual perspective of applicability: planning and operational level. They provide a helpful source of information for wildfire management decision-making and planning design to prepare the landscape to allow firefighters to obtain access and work in fuel breaks, reduce flame length with appropriate fuel treatments, and optimize the location of fuel breaks based on intersection angle between fire and fuel break (ANG). Thus, this research may extend the use of tools such as the Suppression Difficulty Index (SDI) (Rodriguez y Silva. et al. 2020), designed to characterize the difficulty of suppression operations through the assessment of landscape parameters such as accessibility, mobility, penetrability, and fireline construction rates. The optimization of these features in the design of fuel breaks by managers makes them more likely to be used by ground crews. Under uncertain wildfire scenarios and limited budgets (Pacheco and Claro 2018), prioritizing areas to treat is a substantive need (Rytwinski and Crowe 2010; Rodriguez y Silva et al. 2020). Although these decisions are rightly based on experience (O'Connor et al. 2022), forest managers need science-based guidance for defining efficient and economically justifiable fuel break networks (Rytwinski and Crowe 2010; Syphard et al. 2011a; Kalabokidis et al. 2016; Plucinski 2019a; Rodriguez y Silva et al. 2020). Fuel breaks are designed under certain conditions; otherwise, outside them, they could become ineffective. In addition, maintaining the design criteria over time is not enough to guarantee effectiveness. Forests are dynamic and endure many changes, and fuel breaks that were designed with suitable criteria could lose effectiveness over time. Land managers should avoid the risk of falling into a lack of dynamism, flexibility, and adaptation and the inertia of doing what has always been done. At the operational level (suppression), this study can help minimize uncertainty, optimize suppression resources, and support wildfire suppression effectiveness and safe firefighting.

Our study contributes to the almost non-existent literature on the empirical assessment of fuel break effectiveness in real fire events using machine learning methods. The difficulty of model interpretation and utilization makes the development of software or an application desirable. This approach can help to overcome obstacles and generalize its use among land and fire managers.

Conclusions

The main factors affecting fuel break effectiveness in wildfire containment are the type of suppression work executed on fuel breaks, the flame length, and the intersection angle between fire and fuel break. Suppression activities executed on fuel breaks significantly increase effectiveness, especially combining ground-aerial firefighting resources. Aerial resources working alone (aerial drops) are insufficient to ensure high fuel break effectiveness. Flame length negatively influences fuel break effectiveness. Small intersection angles ensure a higher probability of fuel break success in containing fires. Our study contributes to alleviating the lack of knowledge from fuel break effectiveness assessments under wildfire scenarios. Artificial intelligence techniques such as machine learning (artificial neural networks and decision tree) and a classic statistical model (logistic regression) provided reliable results for fuel break effectiveness assessment. Very similar classification percentages were observed between logistic regression, decision tree, and artificial neural network models. While the highest accuracy was observed in the artificial neural network, the decision tree can increase the ease of application by end users due to the tree's straightforward structure and the direct meaning of its nodes and branches. The proposed predictive models can be used to classify fuel breaks according to their effectiveness in containing wildfires. Effectiveness assessment plays an essential role in wildfire management, as it provides conditions for safe and effective firefighting work. The increase in effectiveness supports the operational decision-making process and budget allocation in fire management. Our findings make it possible to address the design and accessibility of new fuel breaks or the revaluation of existing ones, identifying areas where effectiveness could be maximized.

Acknowledgements

We are thankful for the wildfire and suppression data provided by the Andalusian regional fire agency (INFOCA). We are also grateful to the editor and anonymous reviewers who offered valuable insights and assisted us in improving the manuscript.

Authors' contributions

MO contributed to the methodology, formal analyses, data processing, and manuscript writing. FRS contributed to the conceptualization, methodology, and supervision. JRM contributed to the methodology, formal analyses, supervision, and funding acquisition.

Funding

This project received funding from VIS4FIRE (RTA2017-00042-C05-01) and ENFIRES (PID2020-116494RR-C44), both projects from the Spanish Ministry of Science, Innovation and Universities.

Availability of data and materials

Data available on request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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Received: 14 February 2023 Accepted: 21 March 2024
Published online: 23 April 2024

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