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Lessons Learned from Arson Wildfire Incidence in Reforestations and Natural Stands in Spain

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Received: 25 January 2019; Accepted: 28 February 2019; Published: 5 March 2019

Abstract: Wildfires are currently considered the major threat to forests in Mediterranean countries. It has been implied that a large percentage of arson-caused fires in Spain are connected with the extensive reforestation programs implemented between 1940 and 1970. However, no consistent studies have been conducted to study the relationships between arson-caused fires and stand origin. Therefore, the goal of this study was to analyze occurrences and model the influence of forest stand origin (artificial or not) on the development of wildfires in peninsular Spain. Twenty-one neural network models were trained to estimate fire incidence through fire type (surface or crown fire), burned area and total treed burned area, based on stand age (years), canopy cover (%), natural age class (from seedling to mature stages) and fuel type classification. Models were built for reforested stands and natural stands of *Pinus pinaster* Ait., the Mediterranean pines *Pinus sylvestris* L., *Pinus nigra* Arn., *Pinus halepensis* Mill. and *Eucalyptus sp*. L'Hér., or groups of these species, and the resulting models were compared. Reforested stands presented higher fire incidence than natural stands mainly for productive species like *Pinus pinaster* Ait. According to the fire type models, thickets had a large influence in the development of crown fires in reforested stands in a general model for all species, the model with the Mediterranean group of pines, and the *Pinus pinaster* Ait. model. Vertical continuity influenced crown fire propagation in natural Mediterranean pines and in Eucalyptus stands. Presence of shrubs, grasslands and wood slash was related to surface fires in models for both reforested and natural stands. The results suggested that stand origin was influential on fire incidence, at least with regard to fire type and commercial species in the northwestern region of Spain.

Keywords: wildfires; fire type; neural networks; reforested stands; not reforested stands

1. Introduction

During the last decades, more than 95% of the wildfires occurred in Spain and in other Southern European Mediterranean countries were of anthropogenic origin, and over 55% of them were classified as arson-caused fires [1,2]. Arson is not random, and many reasons have been put forward to explain why arsonists burn forests [3]. Among them, Simon et al. [4], Alvarez et al. [5] and Fuentes-Santos et al. [6] have cited resentment against reforestations as a motivation for arson-caused fires. A relationship between arson fires and reforestations is assumed in the Spanish Wildland Fire National Statistics of the Ministry of Agriculture, Fishing, Food and Environment, which includes in the fire reports a code for "Arson fires motivated by resentment against reforestations" [1]. In the past, these arson-caused fires would have been triggered by the discontent of many rural communities for the shifting of their productive and rangelands into forest [7] and towards the wood rights' owner (and thus the beneficiary of the wood's sale) when land and wood differed in ownership [8]. However, other motivations have risen over time; forcing land use changes is a potentially relevant, but difficult to prove, motivation in Southern European countries that depend on the tertiary sector [9]. Regardless of underlying motivation, the relations between arson wildfires and reforestations have received little attention in the literature. Previous studies on general human-caused fires, not specific for arson, have sometimes included forest-related variables like commercial value [10] or species composition [11–15]. Forest stand characteristics are usually accounted for and converted to fuel type categories [16]. Yet, very little scientific evidence exists on how stand origin may affect other drivers and influence arson fire incidence, despite decades-long controversies [8,17,18].

Reforestation has been frequent in many European countries in which clear-cutting [19] and natural disturbances such as windstorms [20] or wildfires [21] have affected large tracks of forest. In addition, socioeconomic drivers from the early 1940s onwards have prompted European Mediterranean countries to implement extensive governmental reforestation programs (i.e., 3 million ha in Spain during 1940–1970, 0.8 million ha after 1952 in Italy, 340,000 ha in Portugal in 1987–1999 [22]). The natural or artificial origin of stands, and later, the effects of natural and anthropogenic disturbances determine forest characteristics, namely, composition and structure. Stand composition and structure are supposed to differ widely between naturally expanding, colonizing stands, and artificially reforested stands that follow different ecological processes [23–25]. Forestry agencies have promoted monospecific and even-aged stands, selecting species for site restoration based on their fast growing and ground cover characteristics [26]. Consequently, reforested forest stands generally have higher even-age tree density and lesser variation of diameter at breast height (DBH), quantity of seedlings, and tree and genetic diversity [18,27].

In Southern European Mediterranean environments, stands arising from secondary succession often share characteristics with reforestations. Land abandonment and wildfires have contributed in Spain to a pervasive and fast expansion of shade-intolerant conifer species [28,29] like Aleppo pine (*Pinus halepensis* Mill.), also used in reforestation for their pioneer capacity. Several authors have stated that wildfires in South Europe have affected mainly conifers, with *Pinus pinaster* Ait., *Pinus halepensis* Mill., and *Eucalyptus sp.* L´Hér. stands reforested in the 1940's and 1950's being comparatively more affected than other species [11–15]. However, in terms of forest structure, wildfires tend to favor high-density even-aged forest stands [27,29], areas of low average tree diameter [12], or undermanaged or abandoned stands, which tend to develop vertical continuity of fuels [30]; it may be argued that both types of stands, either reforested or naturally arising from secondary-succession after abandonment since the 1950s, currently share these features and are both of them potentially highly susceptible to fire [31,32].

Our work aimed to compare the past incidence (occurrence and behavior) of arson-caused fires in reforested and nonreforested fire-prone stands in Spain. We explored fire incidence patterns to discredit or support the notion that reforestations are comparatively more affected by arson, due to resentment or other motivations. Similarity of fire incidence patterns for any stand origin would indicate arson is not specific to reforested stands, and that forest characteristics are alike across natural and artificial stands of fire-prone species determining fire behavior. Dissimilarity of patterns by origin could indicate differences in stand characteristics (behavior) and/or a differential pressure from arson (occurrence), requiring further analysis.

The hypothesis of our study was that stand origin influences ignitions, forest composition and stand structure to produce different patterns in fire occurrence, fire type and burned area. We analyzed fire occurrence, fire type and burned area in reforested and nonreforested stands, based on species composition, natural class age, canopy cover and fuel type.

2. Materials and Methods

The study area encompassed the Spanish mainland, covering around 492,174 km^2 (Figure 1). The predominant Mediterranean climate in Spain, characterized by long summers of high temperatures and low rainfall, contributes to the high risk of fires in the country [33]. The fuel environment has undergone critical changes since the 1950's, with a general increase in continuity and load due to land abandonment and socioeconomic changes, including reforestation [34]. Changes in the futures of fire regimes have been detected in past decades, with noteworthy shifts after the late 1980's and the first half of the 1990's [35]. After the extreme fire events in 1998 in Spain, wildfire policies and management (Law 43/2003, of November 21th) moved to reducing the gap between suppression and prevention budgets in the country, with a temporary increase in forest management interventions that was short-lived. The financial crisis that hit Spain in 2007–2008 [36] undermined the forestry sector, leading to the closing of many industries and, again, to pervasive forest abandonment. However, the crisis also produced a reduced pressure on the land resource for development and construction [37]. This factor may have influenced the occurrence arson wildfires, which decreased from an average of 10,587 arson-fires/year in 1998–2008 to 7336 fires/year in 2009–2015 [1]. The economic recovery of the country is currently leading to fire environmental conditions very similar to the conditions in the pre-financial-crisis period 1998–2008 [1]. Analysis of past patterns may provide clues for exploring future relations between arson fires and forest stand characteristics, determined by their origin, which justifies the selection of 1998–2008 as our study period.

2.1. Reforestation Historical Data

About 54% of Spain is covered by woodlands and shrublands, but only 35% can be considered forest [38]. Reforestations (Figure 1) represent almost 8% of the total land area of Spain [39].

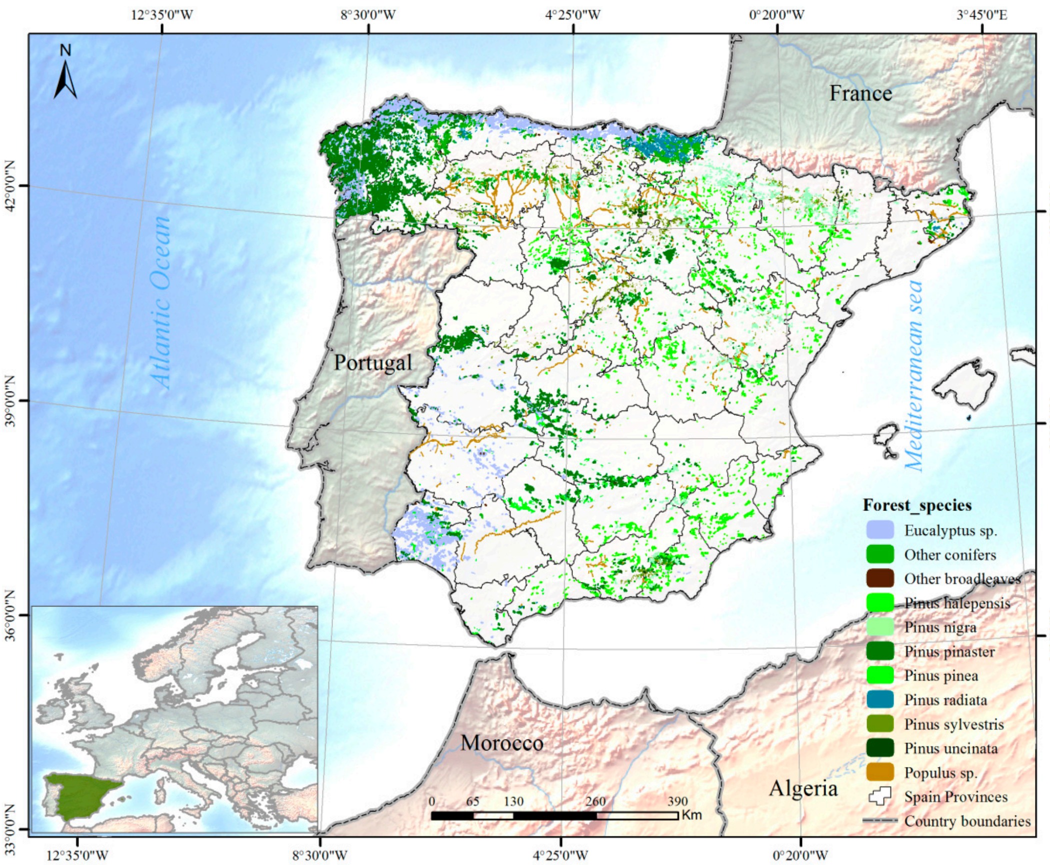

Figure 1. Map of reforested areas in Spain. (Source: adapted from Ruiz de la Torre, 1990)

The Forest Map of Spain used here was made between the years 1986 and 1997 through aerial photographs acquired in 1985 in tandem with field work (II National Forest Inventory, 1:200,000), which made it appropriate for the study period 1998–2008 [40]. According to the Forest Map of Spain, the main reforested species were *Pinus pinaster* Ait. (24.5% of the total reforested area), *Pinus sylvestris* L. (17.3%), *Pinus halepensis* Mill. (14.6%), *Eucalyptus sp.* L´Hér. (13.5%), *Pinus nigra* Arn. (11.8%), *Pinus pinea* L. (6.6%), *Pinus radiata* D. Don. (5.1%), *Populus sp* (1.6%), *Pinus canariensis* C. Sm. (0.8%) and *Pinus uncinata* Mill. (0.5%) with a total reforested area of 3.19 million ha [41].

2.2. Fire Historical Data

The fire registry was obtained from the General Fire Statistics of Spain (EGIF) of the Coordination Centre for National Information on Wildfires (CCINIF) of the Ministry of Agriculture and Fishing, Food and Environment [1]. The total amount of fires recorded during 1998–2008 was 417,406 but only arson fires were considered for the study (130,405 fires). Each fire record provided information on fire type, burned area, total treed-area burned, cause, motivation, species affected, stand mean age, natural age class, percentage canopy cover of the affected vegetation, fuel type, and many other variables related to fire suppression (detection date, arrival time, suppression resources, etc.) and losses caused (i.e. estimated monetary value of the forest products lost).

We selected several dependent (Fire Type—FT: surface/crown fire; Burned Area—BA in ha; and Treed Burned Area—TBA in ha) and independent variables (Table 1) from the EGIF database in agreement with the stated hypothesis. Mean stand age (AGE) was available in the fire reports, but not density, so we selected the percentage of canopy cover (CC) as independent variable. Stand structure was defined through five mutually exclusive natural age classes, from seedlings to mature forest (i.e., seedling—SD, sapling—SS, thicket—TH, pole—PS and high-forest—HFS). The fuel type (FTP1-15) classification used by the EGIF database was also included to compare the relative relevance of the fuel type class versus other forest stand characteristics on the incidence outcome. The EGIF fuel type classification is an adaptation of Rothermel's [42] conducted by the Ministry of Agriculture and Fishing, Food and Environment.

Table 1. Description of the 22 independent variables. The description of the fuel types is according to the EGIF database.

Acronym	Description	Acronym	Description
AGE	Mean Age	FTP5	Grasses and bushes
CC	Canopy cover	FTP6	Grasses and forest
SD	Seedling stage	FTP7	Grasses and slash
SS	Sapling stage	FTP8	Bushes and forest
TH	Thicket stage	FTP9	Bushes and slash
PS	Pole stage	FTP10	Forest and slash
HFS	High-forest	FTP11	Grasses, bushes, and forest
FTP1	Grasses	FTP12	Grasses, bushes and slash
FTP2	Bushes	FTP13	Grasses, forest and slash
FTP3	Forest	FTP14	Bushes, forests and slash
FTP4	Wood slash	FTP15	Grasses, bushes, forest, and slash

2.3. Database for Model Building

Numerical and spatial analysis techniques applied with a dedicated GIS allowed matching ignition points to forest stands by origin. The number of fires located within reforestation polygons (RF) was 21,823 (Figure 2), while 108,582 fires started in nonreforested areas (NRF) in the study period. We removed missing data records and selected only those in which the Forest Map of Spain data was in agreement with the fire report in terms of forest characteristics, which considerably reduced the available data. The available data from 130,405 to 8022 usable records. We sampled arson fires in reforested stands by natural class age category to cover the whole range of characteristics, leaving

4810 RF observations and 3212 NRF observations in the database for analysis. The number of arson fire ignitions in RF and NRF stands were compared by species and weighted by area.

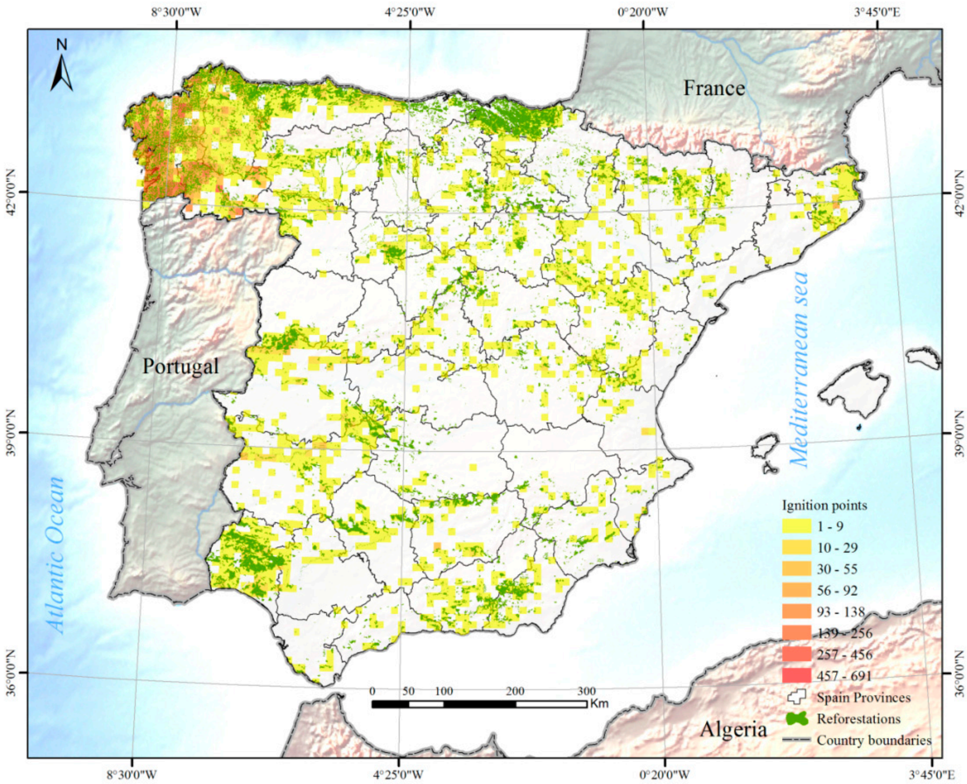

Figure 2. Frequency of ignition points within reforestations in Spain.

Additionally, RF and NRF databases were split by species before fire behavior modeling was carried out. Fire behavior features (Fire Type—FT, Burned Area—BA, and Treed Burned Area—TBA) were modelled separately for RF and NRF stands of the species listed in Section 2.1. RF and NRF *P. pinaster* and RF stands of *Eucalyptus sp.* were also analyzed in separate models. No arson fires in NRF stands of *Eucalyptus sp.* did exist, as this non-native species in Spain is always planted. The pine species *Pi. halepensis*, *P. nigra* and *P. sylvestris* were grouped for model building, based on their geographical distribution allowing mixing in the fringes of contiguous altitudinal levels in continental Mediterranean mountains, and because of a lower number of records available than for *P. pinaster*, the species most used in reforestation in Spain. Because the number of fire records of the other species used in reforestation (*P. pinea*, *P. radiata*, *Populus*, *P. canariensis* and *P. uncinata*) was likewise not large enough to build suitable models, they were also discarded for individual modeling. These species have been used in reforestation less frequently (<7%), but are affected by fire, so they were included in the global models in RF and NRF stands.

The number of fire observations varied for each modeling database (Table 2). The largest data set was for modeling Fire Type (surface/crown) in Reforested Stands (1524 cases) and the smallest was the dataset for modeling Treed Burned Area in Reforested pine stands (40). Databases were as much balanced as possible for numbers of observations in each category for classification.

2.4. The Modeling Approach: Artificial Neural Network (ANN) Models

Models for FT, BA and TBA were built based on any combination of the independent variables in Table 1, for the different species or groups of species (all species, continental Mediterranean mountain pine species, *P. pinaster*, *Eucalyptus sp.*), and forest stand origin (reforested/nonreforested). A total of 21 models (Table 2) were built.

Table 2. Database definition and number of fire observations used for model building.

Dependent Variables	Surface Features	Number of Observations
Fire type	Reforested stands (All species) (RF_FT)	1524
	Not reforested stands (All species) (NRF_FT)	1136
	Reforested Pine sp. (RFPINE_FT)	122
	Natural Pine stands (NRFPINE_FT)	488
	Reforested *P. pinaster* (RFPP_FT)	1054
	Natural stands of *P. pinaster* Ait. (NRFPP_FT)	167
	Eucalyptus sp. (RFE_FT)	330
Burned area	Reforestations (RF_BA)	1291
	Not Reforested stands (NRF_BA)	923
	Reforested Pine sp. (RFPINE_BA)	59
	Natural Pine stands (NRFPINE_BA)	306
	Reforested *P. Pinaster* (RFPP_BA)	886
	Natural stands of *P. Pinaster* (NRFPP_BA)	125
	Eucalyptus sp. (RFE_BA)	298
Total tree burned area	Reforestations (RF_TBA)	924
	Not reforested stands (NRF_TBA)	597
	Reforested Pine sp. (RFPINE_TBA)	40
	Natural Pine stands (NRFPINE_TBA)	146
	Reforested *P. pinaster* (RFPP_TBA)	657
	Natural stands of *P. pinaster* (NRFPP_TBA)	98
	Eucalyptus sp. (RFE_TBA)	192

Artificial neural networks (ANN) were chosen to explore the relationship between stand characteristics and fire behavior because they had proven useful in other wildfire studies, providing good accuracies and generalization capability (i.e., [29,43,44]). When dealing with non-normal distributions of the data, or nonlinear, complex relationships, these models are as reliable as any traditional statistical method, and often more robust [45]. An ANN is an information processing algorithm capable of learning patterns in data by iterative adjustment of the connections between processing elements (nodes) organized in layers. Our models were feed-forward multilayered non-linear fully connected cascade-correlation networks [46], built using NeuralWorks Predict® v.3.24 software [47]. The models were computed as in Alcázar et al. [48] and Debouk et al. [49]. The cascade-correlation algorithm starts model building with the simplest possible architecture, adding nodes until an optimal multi-layer structure is reached [46]. Training was based on an adaptative gradient learning rule, a variant of the general algorithm of back-propagation [50].

The FT models were based on a binary classification (with one-of-N encoding output either Surface Fire (1,0) or Crown Fire (0,1)). The BA and TBA models were predictive providing one output in hectares. Categorical independent variables were input to the network by using the same one-of-N encoding [29]. Interval variables (Age, CC) underwent several transformations that were tested with a genetic algorithm before the actual model training. As usual in ANN learning, each database was divided in three subsets: 10% of the observations were separated to validate the models with data not used in model building. From the rest, 70% were used for training and 30% for testing the accuracy of the model performance and to stop training [51]. Several replicates were simulated for each model. Convergence to a same or similar architecture between the replicates was checked to corroborate robustness of the models. Parsimonious models were favored because of the relatively low number of observations, which generally was below 1000 [48].

The best models were selected according to their capability to explain the dependent variable and performance in terms of total percentage correctly classified and confusion matrix (FT classification networks) and R correlation values between observed and predicted values (BA and TBA prediction networks).

A sensitivity analysis based on the partial derivatives of the outputs with respect to the inputs was run to establish which independent variable had the highest impact on the predicted variable for every model. A higher frequency of selection in the variable selection genetic algorithm was also indicative of the greater relevance of an independent variable.

3. Results

In terms of fire occurrence, the analysis of ignitions started in RF or NRF stands in the study period is presented in Table 3. It is remarkable that the ignition rate of *P. pinaster* is much higher in RF stands than in NRF stands, in a contrary pattern to the other *Pinus* species, with higher rates in natural stands. Planted species *Eucaliptus* and *Populus* also exhibited high rates of ignition, over one per 100 ha.

Table 3. Comparison between the number of ignition points located in reforested and natural stand by species (1998–2008) (source: adapted from Castroviejo et al. [52] and the II National Forest Inventory [53]).

Species	Total RF Surface (ha)	N° Ignition Points in RF (N° Ig/100 ha)	Total NRF (ha)	N° Ignition Points in NRF (N° Ig/100 ha)
P. pinaster	782,414	14,908 (1.90)	517,586	1888 (0.365)
P. sylvestris	552,973	663 (0.11)	227,027	690 (0.304)
P. halepensis	466,282	535 (0.11)	673,718	4850 (0.720)
Eucalyptus sp.	431,012	4633 (0.010)	-	-
P. nigra	378,542	255 (0.06)	165,458	1583 (0.957)
P. pinea	212,761	112 (0.05)	72,239	998 (1.382)
Populus sp.	50,519	695 (1.375)	-	6 Not available
Other hardwoods	30,033	21 (0.69)	-	9 Not available
P. uncinata	17,322	1 (0.05)	32,678	63 (0.193)

As for fire behavior dependent variables, unfortunately none of the prediction models developed for Burned Area and Treed Burned Area complied with the correlation requirements set (R > 0.50) or gave satisfactory enough results to reach significant conclusions. Consequently, only the best classification networks built for Fire Type classification are presented here.

3.1. Models RF_FT and NRF_FT: Fire Type in Reforested and Natural Stands (All Species)

According to Table 4, RF_FT and NFR_FT models present a simple architecture, with no nodes in the hidden layer in the RF_FT model (6-0-2) and only one in the NRF_FT model (8-1-2). The RF_FT model had a higher accuracy (around 0.85 in the training, testing and validation samples), whereas the NRF_FT accuracy model was around 0.7. In both models, the accuracy for crown fires was higher than that for surface fires, which was below 0.5 in the training, testing and validation samples for the nonreforested stands model NRF_FT.

Table 4. Best model architecture and confusion matrix for the classification of Fire Type within reforested and not reforested stands (all species).

N° of Obs.1524	Model RF_FT (network 6-0-2)				
	Accuracy	**Observed**	**Pred. Crown Fire**	**Pred. Surface Fire**	**Total**
Train	0.98	Crown Fire	435	5	440
	0.73	Surface Fire	108	305	413
	0.86	Total	543	310	853
Test	0.96	Crown Fire	175	6	181
	0.73	Surface Fire	50	136	186
	0.84	Total	225	142	367
Valid	0.98	Crown Fire	139	2	141
	0.74	Surface Fire	41	122	163
	0.85	Total	180	124	304
N° of Obs. 1136	**Model NRF_FT (network 8-1-2)**				
Train	0.95	Crown Fire	298	14	312
	0.46	Surface Fire	173	151	324
	0.70	Total	471	165	636
Test	0.95	Crown Fire	126	6	132
	0.41	Surface Fire	83	58	141
	0.67	Total	209	64	273
Valid	0.95	Crown Fire	119	5	124
	0.40	Surface Fire	61	42	103
	0.70	Total	180	47	227

The sensitivity analysis (Table 5) shows that FTP2 (shrubs) and AGE (Stand mean age) variables were selected in both models, being positively correlated to surface fires. FTP2 is the variable with higher weight. Its frequency of selection is very high in both models (with a percentage of 0.94 and 0.75, respectively). The best RF_FT model also shows that a higher proportion of TH (thickets) and PS (pole-stage forests) increases crown fire hazard, whereas AGE, FTP2 (shrubs) and FTP6 (forest with grasses) favor surface fires in reforested stands.

In the NRF_FT model for natural stands, only CC (canopy cover) is related with the development of crown fires. FTP1 (grasses), FTP2 (shrubs) and FTP4 (wood slash) were the most important variables for the development of surface fires in natural stands.

Table 5. Sensitivity analysis of the best models for the classification of Fire Type within reforested and not reforested stands (all species).

Input variables in the best RF_FT model						
	FT	AGE	TH	PS	FTP2	FTP6
Average	Crown fire	−0.0328	0.0305	0.0218	−0.5766	−0.0622
	Surface fire	0.0328	−0.0305	−0.0218	0.5766	0.0622
		AGE	TH	PS	FTP2	FTP6
Variance	Crown fire	0.0013	0.0004	0.0002	0.1426	0.0016
	Surface fire	0.0013	0.0004	0	0.1426	0.0016
Frequency		0.69	0.65	0.96	0.94	0.93

Input variables in the best NRF_FT model									
	FT	AGE	CC	SS	HFS	FTP1	FTP2	FTP3	FTP4
Average	Crown fire	−0.205	0.097	−0.008	−0.025	−0.917	−0.618	−0.076	−0.493
	Surface fire	0.205	−0.097	0.008	0.025	0.917	0.6182	0.076	0.493
		AGE	CC	SS	HFS	FTP1	FTP2	FTP3	FTP4
Variance	Crown fire	0.01	0.001	9.013	7.719	0.098	0.0448	0	0.028
	Surface fire	0.01	0.001	9.013	7.719	0.098	0.0448	0	0.028
Frequency		0.75	1	0.25	0.22	0.27	0.75	0.25	0.4

*3.2. Models RFPINE_FT and NRFPINE_FT: Fire Type in Continental Mediterranean Mountain Pines in Reforested and in Natural Stands (*P. halepensis, P. nigra, P. sylvestris*)*

RFPINE_FT and NFRPINE_FT models present a simple architecture (Table 6), with no nodes in the hidden layers. The RFPINE_FT model accuracy was 0.82 and the accuracy of the NFRPINE_FT model 0.67. In both models, crown fires accuracy was higher than surface fires accuracy, especially in the RFPINE_FT model.

Table 6. Best model architecture and confusion matrix for the classification of Fire Type for continental Mediterranean mountain pines in reforested and natural stands.

N° of Obs. 122		Model RFPINE_FT (network 9-0-2)			
Data Subsets	**Accuracy**	**Observed**	**Pred. Crown Fire**	**Pred. Surface Fire**	**Total**
Train	0.82	Crown fire	23	5	28
	0.72	Surface fire	11	29	40
	0.76	Total	34	34	68
Test	0.7	Crown fire	12	5	17
	0.69	Surface fire	4	9	13
	0.72	Total	16	14	30
Valid	0.62	Crown fire	10	6	16
	0.12	Surface fire	7	1	8
	0.7	Total	17	7	24
N° of Obs. 488		**Model NRFPINE_FT (network 7-0-2)**			
Train	0.67	Crown fire	86	42	128
	0.55	Surface fire	64	81	145
	0.61	Total	150	123	273
Test	0.67	Crown fire	42	20	62
	0.55	Surface fire	25	31	56
	0.61	Total	67	51	118
Valid	0.64	Crown fire	35	19	54
	0.6	Surface fire	17	26	43
	0.62	Total	52	45	97

Table 7 shows that FTP2 (Shrubs) was selected in the best RFPINE_FT and NRFPINE_FT as in the general (all species) models, being positively associated to surface fires. CC (canopy cover), FTP11 (forests with shrubs and grasses) and FTP15 (forests with shrubs, grasses and slash) were also selected in both models, but were positively correlated with crown fires.

According to Table 7, the best RFPINE_FT model shows that the development of crown fires in reforested pine stands is higher in those forests with a higher AGE, CC (canopy cover), TH (thicket stage), FTP11 (forests with shrubs and grasses) and FTP15 (forests with shrubs, grasses and slash). On the contrary, a higher probability of surface fires in RF pine stands is associated to a higher percentage of FTP2 (shrubs) and FTP4 (wood slash). The variables TH (1), AGE (0.92), and CC (0.90) had the higher frequency of selection by the genetic algorithm.

The highest probability of crown fires in the best NRFPINE_FT model is mainly related to a higher percentage of CC, FTP8 (bushes and forest), FTP11 (forests with shrubs and grasses) and FTP15 (forests with shrubs, grasses and slash). Surface fires are mainly related to FTP2 (shrubs). FTP2, FTP8, TH and CC are the variables most frequently selected for these models by the genetic algorithm applied to variable selection.

Table 7. Sensitivity analysis of the best models for the classification of Fire Type within reforested and not reforested stands (Pine Group).

Input variables in the best RFPINE_FT model								
	FT	AGE	CC	TH	FTP2	FTP4	FTP11	FTP15
Average	Crown fire	0.829	0.228	0.207	−0.234	−1.055	0.045	0.096
	Surface fire	−0.829	−0.228	−0.207	0.234	1.055	−0.045	−0.096
		AGE	CC	TH	FTP2	FTP4	FTP11	FTP15
Variance	Crown fire	0.236	0.006	0.005	0.006	0.119	0	0.001
	Surface fire	0.236	0.006	0.005	0.006	0.119	0	0.001
Frequency		0.92	0.85	1	0.52	0.83	0.35	0.45
Input variables in the best NRFPINE_FT model								
	FT	CC	SS	PS	FTP2	FTP8	FTP11	FTP15
Average	Crown fire	0.198	0.003	−0.007	−0.318	0.091	0.105	0.066
	Surface fire	−0.198	−0.003	0.007	0.318	−0.091	−0.105	−0.066
		CC	SS	PS	FTP2	FTP8	FTP11	FTP15
Variance	Crown fire	0.001	0	0	0.002	0	0	0
	Surface fire	0.001	0	0	0.002	0	0	0
Frequency		0.93	0.38	0.67	1	1	0.71	0.71

3.3. Models RFPP_FT and NRFPP_FT: Fire Type in P. pinaster *in Reforested and in Natural Stands*

RFPP_FT and NFRPP_FT models present a simple architecture (Table 8), with no nodes in the hidden layers (9-0-2 and 7-0-2, respectively).

Table 8. Best model architecture and confusion matrix for the classification of Fire Type within reforested and not reforested stands of *P. pinaster*.

N° of Obs. 1053	**Model RFPP_FT (network 6-0-2)**				
Data Subsets	**Accuracy**	**Observed**	**Pred. Crown Fire**	**Pred. Surface Fire**	**Total**
Train	0.98	Crown Fire	270	5	275
	0.79	Surface Fire	66	249	315
	0.87	Total	336	254	590
Test	1	Crown Fire	128	0	128
	0.81	Surface Fire	23	102	125
	0.9	Total	151	102	253
Valid	0.97	Crown Fire	103	3	106
	0.77	Surface Fire	23	81	104
	0.87	Total	126	84	210
N° of Obs. 166	**Model NRFPP_FT stands (network 5-2-2)**				
Train	0.98	Crown fire	57	1	58
	0.71	Surface fire	10	25	35
	0.88	Total	67	26	93
Test	0.9	Crown fire	19	2	21
	0.73	Surface fire	5	14	19
	0.82	Total	24	16	40
Valid	0.83	Crown fire	15	3	18
	0.6	Surface fire	6	9	15
	0.72	Total	21	12	33

The accuracy in both models followed the same pattern as in previous results (but better than the accuracies of previous models, Tables 4 and 6), and were better for artificial stands (accuracy around 0.88 in RF and 0.80 in NRF stands) and crown fires (0.98–0.90 in crown fires and 0.80–0.70 in surface fires).

Table 9 shows that FTP2 was selected in the best RF and NRF *P. pinaster* models as in the previous models, also being associated to surface fires. The RFPP_FT model shows that the development of crown fires in *P. pinaster* stands is higher in those forests with higher percentage of TH (thicket), SS (sapling) and PS (pole) stages and the development of surface fires is more likely with a higher proportion of CC, SD (seedlings) and FTP2 (Shrubs). SD (0.86) and CC (0.64) are the variables with the highest frequency of selection in the RFPP_TF model.

Table 9. Sensitivity analysis of the best models for the classification of Fire Type within reforested and not reforested stands (*P. pinaster*).

Input variables in the best RFPP_FT model							
	FT	CC	SD	TH	SS	PS	FTP2
Average	Crown fire	−0.092	−0.012	0.021	0.022	0.001	−0,499
	Surface fire	0.092	0.012	−0.021	−0.022	−0.001	0,499
		CC	SD	TH	SS	PS	FTP2
Variance	Crown fire	0.004	7.183	0	0	1.611	0,122
	Surface fire	0.004	7.183	0	0	1.611	0,122
Frequency		0.64	0.86	0.21	0.32	0.36	0,57

Input variables in NRFPP_FT model						
	FT	HFS	FTP1	FTP2	FTP5	FTP9
Average	Crown fire	−0.997	−0.213	−0.578	−1.273	−1.069
	Surface fire	0.997	0.213	0.578	1.273	1.069
		HFS	FTP1	FTP2	FTP5	FTP9
Variance	Crown fire	0.303	0.013	0.102	0.495	0.348
	Surface fire	0.303	0.013	0.102	0.495	0.348
Frequency		1	0.31	0.92	0.54	0.66

The NFRPP_FT model identified high probability of surface fires (or low of crown fires) with higher presence of HFS (high-forest, mature stage), FTP1 (grasses), FTP2 (shrubs), FTP5 (grasses and shrubs) and FTP9 (shrubs and wood slash), with HFS (1) and FTP2 (0.92) being the most often selected variables.

3.4. *Models RFE_FT:* Eucalyptus *Artificial Stands*

The best RFE_FT model presents a simple architecture, with six inputs, no hidden nodes, and two outputs (Table 10).

Table 10. Best model architecture and confusion matrix for the classification of Fire Type in *Eucalyptus* sp.

N° of Obs. 330	**Model RFE_FT (network 6-0-2)**				
Data Subsets	**Accuracy**	**Observed**	**Pred. Crown Fire**	**Pred. Surface Fire**	**Total**
Train	0.95	Crown fire	83	4	87
	0.77	Surface fire	22	75	97
	0.85	Total	105	79	184
Test	0.92	Crown fire	38	3	41
	0.84	Surface fire	6	33	39
	0.88	Total	44	36	80
Valid	0.96	Crown fire	30	1	31
	0.74	Surface fire	9	26	35
	0.84	Total	39	27	66

The best model RFE accuracies were over 0.84 for the training, testing and validation subsets, with higher crown fires accuracy (over 0.92) than surface fires accuracy (over 0.80). The RFE_FT model (Table 11) shows that crown fires in *Eucalyptus* stands are directly related to FTP8 (shrubs and forest), FTP3 (forest) and FTP6 (grasses and forest). Surface fires are positively linked mainly to CC and FTP9 (shrubs and slash). In the RFE_FT variable selection, FTP3 (0.91), FTP8 (0.81) and AGE (0.8) were most often selected.

Table 11. Sensitivity analysis of the best model for the classification of Fire Type within reforested stands of *Eucalyptus* sp.

		Input Variables in the Best RFE_FT Model					
	FT	AGE	CC	FTP3	FTP6	FTP8	FTP9
Average	Crown fire	−0.004	−0.097	0.361	0.348	0.514	−0.05
	Surface fire	0.004	0.097	−0.361	−0.348	−0.514	0.05
		AGE	CC	FTP3	FTP6	FTP8	FTP9
Variance	Crown fire	0.002	0.006	0.078	0.072	0.158	0.001
	Surface fire	0.002	0.006	0.078	0.072	0.158	0.001
Frequency		0.8	0.5	0.91	0.25	0.81	0.56

4. Discussion

This study focused on the past incidence of arson wildfires in artificial and natural stands, within a time frame providing a fire environment that is very likely to reproduce in the next few years in Spain. In order to learn our lessons, ignition points obtained from fire history records between 1998 and 2008 were overlapped with the National Forest Map of Spain at that time, to better understand occurrence and fire behaviour patterns in this study period.

4.1. Wildfire Incidence: Occurrence in Reforested and Nonreforested Stands

When considering the number of ignition points in relation to the origin of forest stands (reforested or natural) and species composition, we found that *P. pinaster* indeed presented relatively more arson ignitions in reforested than in nonreforested stands than expected based on its respective area of distribution. On the contrary, proportionally more arson-caused forest fires occurred in natural stands of *P. halepensis*, *P. nigra*. and *P. pinea* than in their reforested stands. *P. sylvestris* and *P. uncinata* presented a similar proportion of arson fire ignitions in stands of any origin.

Though some authors stated in previous work that wildfires in South Europe have affected mainly conifers reforested in the 1940's and 1950's (*P. pinaster*, *P. halepensis*, and *Eucalyptus sp.* stands) [11–15], and others [6–8] indicated reforestations as a major factor of occurrence of arson wildfires in Spain, we found this only true for a few of the most productive and fast-growing species. Reforestations per se were not comparatively more affected by arson unless we considered regional location. The spatial distribution of arson fires (Figure 2 and reference [1]) reveals that the highest percentage of these was located in the Northwestern (NW) region of Spain, where there was a differential pressure of arson on stands of different origin. In NW Spain, *P. pinaster* and *Eucalyptus sp.* are the most common species for reforestation, based on commercial value, and human-caused fire occurrence is high [6]. According to Cabana Iglesia [8], NW Spain has seen many occurrences of arson as a form of protest by rural communities in favor of the return of communal forests to the traditional silvopastoral use. Consequently, if this was the underlying motivation, arson occurrence may not have been species-specific, but location-specific, linked to wildlands ownership and land use issues.

On the other hand, the Mediterranean region, especially near the Eastern coastal mountains, has the highest percentage of monospecific and mixed Aleppo pine forest in the country [18], but a large part of the area can be considered as natural forests (from secondary succession), and arson seems to prefer them to reforested stands. Aleppo pine stands in the coastal Mediterranean region are more affected by human-caused fires [1] than Aleppo pine stands in the hinterland, so again, location-specific drivers could explain occurrence patterns. In the Mediterranean, drivers were probably linked to development demands for land, but the general difficulty in the certain identification of motivations and causes for arson makes risky to make assumptions, and precludes analysis beyond the scope of this work.

Thus, other risk factors related to human-caused fire occurrence, like low drought vegetation moisture [16], weather indices [54], traditional agricultural practices [15] or presence of long-term serial fire-setters as suggested by Fuentes-Santos et al. [6] could be better variables for explaining occurrence patterns than stand´s origin or composition.

4.2. Wildfire Incidence: Neural Network Models for Fire Behaviour

Modelling the relationship between fire type and a set of different independent variables was successfully achieved by means of cascade-correlation artificial neural networks. The neural networks were parsimonious, robust, and converged in all cases to same/similar solutions when the observations were randomly interchanged in the training, test and validation subsets, and when the initial random weights were shifted [45]. However, no robust and reliable models were found for total burned area and treed burned area. This was probably the consequence of having one single set of forest structure parameters for all the burned area in one single fire. There may be a high diversity in forest structures typically affected by any single fire in Spain, but only one description is input in the fire reports, which prevented the successful development of these models.

The fire type models did allow us to explore stand-origin influences; models for artificial and natural stands were different in accuracy, structure, and variables selected. Tables 4, 6, 8 and 10 showed that crown fires exhibited better classification accuracy than surface fires in all the databases.

Out of all datasets and corresponding models, the best accuracy was obtained for the *P. pinaster* models, the species most extensively used for reforestation (24% of the reforested area), especially in the NW Spain, and the most affected by human-caused fires. Artificial seedlings of this species experimented surface fires, but thickets, young forest and pole-forest were linked to crown fires. Closed canopy cover seemed to favor surface fires [29], a trend contrary to the Mediterranean pines group [25], but understandable by the higher foliage density and thickness of this pine needles and their shadowing effects. Surface fires were related to the presence of shrubs, grasses, and slash in the under-story of high-forest in natural maritime pine stands.

The analysis performed on the continental Mediterranean pines indicated an opposite trend with regards to stand age. Crown fires were more likely to occur in pine reforestations when the stand age increased with closed canopy cover and vertical fuel continuity. Natural stands showed similar trends for canopy cover and verticality in fuels, but thickets were not selected as a crown fire factor, neither was age an input to the model. This may be explained by the fact that more natural conditions in the establishment of these stands mean that age is not coetaneous, competition among individuals is lower and thickets are not so homogeneous spatially [55].

Eucalyptus planted stands appeared to be more prone to crown fires when vertical continuity was present (forest, or forest with grasses and shrubs) but also a somewhat lower canopy cover. Surface fires seemed more likely with denser canopy cover, increasing age of the stands, and presence of shrubs and slash. In any case, presence of shrubs and slash is quite common in *Eucalyptus* stands, as the combination of abundant understory vegetation due to the Atlantic geographic location of the *Eucalyptus* plantations often combined with woody debris coming from silvicultural activities, frequently applied due to importance of the pulp market in the area (Galicia). When a flammable young tree layer is added over this understory, crown fires result [56].

Since different variables were selected in each model, the formulated hypothesis stated that the origin of a forest stand influences species, age, density and structure, and in turn fire type was upheld. According to the obtained results, fire type was influenced by different variables in stands of different origin and species. Thickets were influential on crown fires in reforestations within the models for all species. Crown fire probability on a forest stand also increased in previous work with smaller tree diameters, larger basal areas and an increasing variation in tree diameter, which suggest thicket structures with high densities [12,14,57]. According to Moreno et al. [58], vertical continuity between understory vegetation (with or without grasses) and trees in pine and eucalypt stands was also linked to crown fires. The variables related to stand age, canopy cover, stand structure, and other fuel types showed variable patterns, but shrubs, grasses and wood slash proved influential for surface fires in all the models. Similar results were found by [59,60], in which fire type in mature stands was linked to the quantity and availability of fuel in their understories. The association of shrubs and surface fires, which was detected in most of the models, is a well-known fact in Spain, and is the basis for the fuel treatments usually applied for hazard reduction (i.e., [61]). General trends for all forest types and origins indicate that the presence of grasses and slash, without brushes and thickets, also favors surface fires (Tables 4, 6 and 8).

Management implications useful for silvicultural treatments and for supporting restoration strategies and policies could be derived from the historical analysis of arson incidence, reinforcing some recommendations by other authors (e.g., [62]) and introducing other actions that may be quite relevant if future conditions evolve as expected in the socioeconomic and ecological environment of Spain. Fuel management is technically well developed in European Mediterranean countries and in Spain, and abundant literature exists on the application of prescribed burning, mechanical thinning or mastication [63,64], but treatments and effects are usually analyzed for individual species (i.e., *P. nigra*, Piqué and Domenech [65]; *P. halepensis*, Palmero-Iniesta [66]; *P. pinaster*, Molina et al. [67] without considering stand origin. In agreement with these findings, aged, more mature forest structures and closed canopy cover generally lead to less severe fires in our models, even in *Eucalyptus* or *P. pinaster* stands, but not in *P. halepensis*, *P. nigra* and *P. sylvestris* forests if vertical fuel connectivity was present. However, our results indicate that controlling understory vegetation influences the development of surface fires especially for shrubs in artificial stands, so treatments should be prioritized in them. Previous work has often grouped several pine species [63], but we found that beyond species, also origin makes a difference in fire behavior. Thickets in artificial stands are the most hazardous structures, especially for our grouped pine species, but this does not seem to be the case for natural stands. Consequently, at the landscape planning scale, thinning in thicket structures should be prioritized for reforested over natural stands.

Dissimilarity of models for stands of different origin (fire type explained by different explanatory variables) seemed to indicate differences in stand characteristics ruled fire behavior. However, and mainly in terms of occurrence, a differential pressure from arson can also explain incidence, so further analysis should be conducted in this regard.

5. Conclusions

This study aimed to learn from the historical (1998–2008) relationship between arson fire incidence (occurrence and behavior) and reforestations in Spain, to anticipate similar future conditions in the fire environment. We intended to discredit or support the notion that reforestations were comparatively more affected by arson. The hypothesis of our study was that stand origin influenced ignitions, forest composition and stand structure to produce different patterns in fire occurrence, fire type and burned area. We analyzed fire occurrence, fire type and burned area in reforested and nonreforested stands, based on species composition, natural class age, canopy cover, and fuel type.

Arson-caused ignitions had a higher rate of occurrence in reforestations of *P. pinaster*, than in its natural stands, but this preference applied only to these commercial species located NW Spain, not to all considered, everywhere.

According to ANN models built for fire type, thickets had a large influence in the development of crown fires in reforested stands in a general model for all species, the model with the Mediterranean group of pines, and the *P. pinaster* model. Vertical continuity influenced crown fire propagation in natural Mediterranean pines and *Eucalyptus* stands. Presence of shrubs, grasses, and wood slash was related to surface fires in models for both reforested and natural stands. The results from this study could not confirm a direct relationship between arson fires and reforestations. However, overall outcomes suggested that stand origin and composition were influential on fire incidence, at least in regards to number of ignitions and fire type.

Future studies should consider additional variables related to location, such as ownership, land uses, topography or weather to improve the accuracy and reliability of models. Understanding arson fire incidence can provide valuable information to support restoration strategies and policies, and also differential management actions over natural and artificial stands. Environmental benefits when implementing restoration programs should consider fire impacts over time, and past lessons.

Author Contributions: E.D.P. processed the wildfire data, generated the neural network models, analyzed the results and contributed to the writing of the manuscript. S.C.-A. contributed to the processing of fire data and the writing of the manuscript. C.V.-G. was involved in research design; develop of the manuscript, methodological guidance for data processing and a critical revision of the manuscript.

Funding: This research received no external funding.

Acknowledgments: We are thankful to Jesús Pemán and Domingo Molina, from the University of Lleida, for helpful suggestions and Marta López, from the Coordination Centre for National Information on Wildfires (CCINIF) of the Ministry of Agriculture and Fishing, Food and Environment (MAPAMA), for helping us in understanding the EGIF database.

Conflicts of Interest: The authors declare no conflicts of interest.

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