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Analysis of Wildfire Susceptibility by Weight of Evidence, Using Geomorphological and Environmental Factors in the Marche Region, Central Italy

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Abstract: Fires are a growing problem even in temperate climate areas, such as those in Central Italy, due to climate change leading to longer and longer periods of drought. Thus, knowing the fire susceptibility of an area is crucial for good planning and taking appropriate countermeasures. In this context, it was decided to use only causal factors of a geomorphological and environmental nature in order to obtain a fire susceptibility analysis that can also be applied to climatically under-sampled areas. Vector data of fires in Central Italy from 2005 to 2023 were collected, and the correct areal extent was calculated for each. At the same time, six factors were selected that could have an influence on fire development, such as ecological units, topographic wetness index (TWI), geology, slope, exposure, and altitude. The model was obtained by means of the weight of evidence statistical method, which takes into account past data by reinterpreting them in a future-oriented way on the basis of the identified factors and classes. The model was validated with a test sample and shows an area under the curve (AUC) value of 0.72 with a reliability that can be described as good considering the total absence of climatic factors that are known to play a major role in fire development. Furthermore, the identified causal factors were divided into classes, and these were carefully weighted in order to define their relative influence in the study area. Particularly Ecological Units with characteristic and well-defined contrast (C) values, which could lead to a more complete definition of forests that tend to increase fire susceptibility and those that tend to decrease it, allowing the latter to be exploited as a hazard mitigation agent.

Keywords: GIS; wildfire; WoE; AUC; TWI; susceptibility; Central Italy; ecological units

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1. Introduction

1.1. Worldwide Wildfire Situation and Trends

Wildfires are a growing problem for nations affected by them, with a spike in number of extreme fires in recent years making the media headlines due to the great damage they cause and the disruption to the ecosystem they affect [1]. Numerous studies show that in various areas of the globe, fires are larger and more destructive precisely because of the nature of the areas themselves, which exacerbate certain characteristics such as the direction and speed of the wind that can lead to a more rapid and intense spread of the fire [2]. However, it appears to be quite common for much of the world to see an increase in extreme wildfires, especially in recent years, as observed in South America, Australia, Canada, the USA, Portugal, and Greece [3,4]. The trend of fires, such as extreme fires, is clearly on the rise, as evidenced by numerous studies in various parts of the world. In the USA, the trend is strongly increasing. For example, from 2000 to 2019, there was an increase in the area affected by fires of about 1000 acres on average [5]. Likewise, in Serbia, there is an increasing trend in terms of fires, with the exception of West Siberia, where the trend is negative [6]. This rather generalised worldwide growth in fires contributes to further problems, such as carbon emissions, accelerated erosion, and other geomorphological environmental hazards [7,8].

1.2. State of the Art Concerning Causal Factors and Fire Modelling

Wildfires are caused by many factors, such as climate, types of ecological units, and the geological-geomorphological situation of the area. Climatic factors such as precipitation, temperatures, soil moisture, evapotranspiration, solar radiation, wind intensity, and direction all have a direct influence on fire generation. Certainly, drought is the most responsible factor in fire generation and is highly correlated to the duration of the drought event, so inevitably, climatic factors are linked to this concept. For example, temperature is an accelerating factor in evapotranspiration, while precipitation produces an increase in humidity both in the air and on the ground. Soil moisture is crucial in wildfires and also depends on the type of soil in the area and solar radiation, which in numerous studies has shown a significant correlation with fire generation [9]. Even wind from the literature shows some influence in fire generation; in fact, its intensity increases the chances of ignition, while the direction is influential because air masses arriving over a given region, depending on where they come from, pass over different areas, gaining or losing moisture [10]. In the same way as climatic causal factors, ecological units are very influential in fire generation, as there are areas of trees, shrubs, grasses, arable land, or other man-made areas that determine a greater or lesser susceptibility to the development of wildfires [11]. In addition to the aforementioned factors, the topography of the terrain is of great importance in the development of fires, which may favour preferential directions for fire or natural barrages. In particular, altitude, slope, and exposure can play a decisive role in increasing or decreasing the possibility of a fire occurring. In fact, certain topographical characteristics may favour an increase in wind intensity, a greater reduction in humidity in certain areas, or even greater possibilities of development of certain plants that are more or less predisposed to fire risk than others. In some cases, there may be indices that tend to highlight characteristics that topographical features are not expressed, such as the topographic roughness index (TRI), or that makes it possible to evaluate how topography responds to climate, as in the case of the topographic wetness index (TWI). Finally, another non-negligible parameter is the soil and substrate, which in turn can influence other factors such as the development of certain plant species or increased moisture retention in the soil, which acts as a mitigating factor in fire risk. These factors are very often used in the literature to create models to help predict the areas most exposed to wildfire hazards [12]. Therefore, statistical models attempt to assess fire susceptibility and can be of two types: deterministic and stochastic [13]. Basically, deterministic methods must be based on a deep a priori knowledge of the phenomenon to be reliable, whereas stochastic methods require less knowledge to be reliable. Very often, it is not possible to know the exact weight that the various factors may have in a phenomenon. Indeed, research arises precisely from the need to understand how influential the factors analysed actually are, so it follows that stochastic methods seem to give the best results. There are many stochastic methods that can be used to define susceptibility to some hazards, such as extreme machine learning [14], random forestry, the weight of evidence [15], Monte Carlo simulation, etc. Statistical methods need to identify the causal factors related to the increased probability of a fire developing in a given area in order to define the susceptibility. Some of these include topographic ones, such as slope, exposure, altitude, topographic wetness index (TWI), and topographic roughness index (TRI); others may take vegetation into account through monitoring aimed at defining ecological units or through satellite indices such as NDVI, SAVI, etc. [16,17]. There are two more recently introduced indices such as the TWI, which simulates water concentration taking into account topography alone and consequently determines a greater or lesser possibility of burning vegetation; instead, the TRI measures the topographical variability of the landscape, which may or may not favour forest fires [18,19]. Other factors are aimed at considering land use, others, soil properties, and geology of the study area [20]. However, most research uses climatic factors, which, as we know, have a determining effect on fire generation and propagation [21]. In fact, models based on climatic factors such as temperature, precipitation, air and soil humidity, solar radiation, or wind are usually more accurate in defining susceptible areas [22]. However, any type of statistical model aimed at areal wildfire susceptibility analyses must be supported by GIS software (ArcGis 10.8) in order to combine the weight of the factors and allow them to be mapped on the territory [23]. This research aims to assess the different weights that environmental and geological-geomorphological criteria may have in fire generation and to hypothesise the physical reasons for these differences. In particular, it was decided not to deal with the climatic part in order to be able to propose this model as possibly valid even in climatically poorly sampled areas, evaluating the performance of a model based only on geological-geomorphological and environmental factors. The goal was to obtain a fire susceptibility map, with a fire database covering 18 years, from 2005 to 2023, and 890 mapped events equal to an area of 71.94 km^2 burnt. Crucial was the use of a stochastic method such as the weight of evidence (WoE), chosen for the good results observed in defining susceptibility to calamitous events in many different areas and the ability to handle multiple information; it represents a robust model for the study of natural hazards [24]. The WoE was primarily used by the biomedical sciences, but the potential of summarising and interpreting scientific needs in relation to risk has allowed for successful adaptation to environmental science issues [25]. In particular, the scientific literature on the subject has shown how the WoE applied to forest fire risk has even higher AUC values and provides better results than other geostatistical methods [26,27]. The WoE was developed and subsequently applied to the study area using GIS software in order to obtain a spatialisation of fire susceptibility. The innovativeness of the research lies mainly in the choice of the geological-geomorphological and environmental factors used, with particular reference to the careful analysis of the ecological units for the entire study area and in the aggregation of geological formations into lithological types. The discrimination of the plant species that constitute the flora of this area is fundamental for understanding their possible natural propensity to generate fires. Usually, wildfire susceptibility analyses include a climatic part that is very well correlated with fire generation [28]. Hence, it is crucial to understand the contributions that other types of factors can make before assessing the triggers. In the future, it would be interesting to assess how much the model's performance can be improved by introducing some climate variables or indices, including satellite ones.

2. Materials and Methods

2.1. Study Area

The Marche region in Central Italy has a wide biodiversity dictated by the topographical variety, which is reflected in a rather marked climatic difference between the various areas dictated by the Apennine chain, as well as by exposure during the winter to winds from the East [29]. The Marche region is not particularly susceptible to fires, although there are years when they are particularly relevant, especially in recent years; also, due to climate change, critical situations are increasing in terms of area and number. In this context, although not exposed to excessively high levels, for this average populated region with valuable crops [30,31], fires represent a risk that should be anticipated and possibly mitigated.

The study area is the Marche region, a territory bordered by the Adriatic Sea to the east and the Umbro-Marchigiano Apennines to the west (Figure 1). The Marche region has a surface area of more than 9000 km^2, and around 1,500,000 people live there.

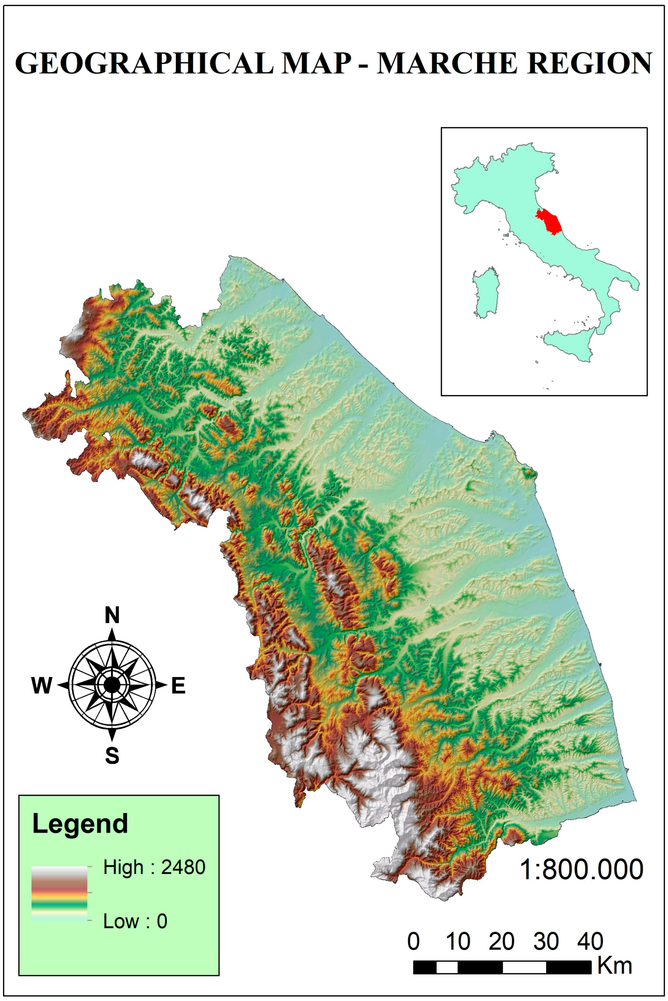

Figure 1. Geography of the Marche region.

The fire risk for this region is not very high, also due to the fact that only part of the region falls fully within the Mediterranean climate with hot, dry summers and sufficient rainfall during the rest of the year. However, climate change, which is leading to increasingly higher temperatures and lower rainfall concentrated in a shorter interval of days, means that the risk of fires in this region is not very high [32]. The Marche region has a high biodiversity in relation to the size of its territory as, due to the altimetric differences ranging from the 2500 m of the highest mountain to the coastal area passing through a wide hilly strip, it has developed many environments that inevitably influence the flora in its adaptation [33].

2.2. Data

The study of fire susceptibility in the Marche region involved several stages. Firstly, wildfire data from 2005 to 2023 were collected. The interval of 18 years was chosen because it is the digitised and freely accessible data that the regional civil protection department makes available. The fire data are polygonal vector files in shapefile format; they were verified one by one by evaluating the dimensions noted in the attribute table and the original paper drawing of the survey on the regional technical map. This validation procedure made it possible to eliminate a number of errors in the attribute table with areas that, in some cases, were larger than what was actually recorded, and in rare cases, the georeferencing was also revised because it did not agree with the drawing on the regional technical map.

This resulted in 890 fires and a burnt area of 71.9 km^2 over the 18 years analysed. Subsequently, the ecological units layer, mapped by the Marche region, was overlaid, and the data were extracted with GIS software to obtain a complete mapping of the ecological units for each fire. The same procedure was adopted for each of the other factors used in the calculation of fire susceptibility, starting with altitude, slope, exposure, topographic wetness index, and the geology of the area. Data compiled by the Marche region were used to obtain the geology, while a digital elevation model at 20 m resolution compiled by the Italian Military Geographic Institute was used to extract all types of topographical and geomorphological data.

2.3. Methods

Six factors were identified for the fire susceptibility analysis: ecological units, TWI, geology, slope, exposure, and altitude. The factors with continuous values were merged to form classes, while the ecological units were not changed because they were already consistently subdivided (Table 1). The lithological formations were also grouped into classes, as subdividing each formation, even those with very similar mineralogical composition, would have led to a lack of significance in the analysis, so they were grouped on the basis of the lithological macrotypes (Figure 2) already summarised in previous research on the subject [34].

Table 1. Classes for each of the factors selected for analysis.

<table>
<tr><th colspan="6">Ecological Units</th></tr>
<tr><td>Airport</td><td>Deciduous shrubland</td><td>Evergreen shrubland</td><td>Bare area</td><td>Roads</td><td>Mixed deciduous woodland</td></tr>
<tr><td>Hornbeam woodland</td><td>Coniferous woodland</td><td>Riparian woodland</td><td>Badland</td><td>Wood of chestnuts</td><td>Quarry</td></tr>
<tr><td>Arboreal cultivation</td><td>Continuous built-up area</td><td>Scattered built-up area</td><td>Beechwood</td><td>Herbaceous heter. form.</td><td>Shores and beaches</td></tr>
<tr><td>Arboreal formation</td><td>Wasteland</td><td>Lake</td><td>Holm oak</td><td>Poplar forest</td><td>Prairie</td></tr>
<tr><td>Pre-forest</td><td>Decidual oak</td><td>Seedlet</td><td>Aquatic vegetation</td><td>Psammophilous vegetation</td><td>Riparian vegetation</td></tr>
<tr><td>Urban green</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><th colspan="6">TWI</th></tr>
<tr><td>0–5</td><td colspan="2">5–10</td><td>10–15</td><td colspan="2">15–20</td></tr>
<tr><th colspan="6">Geology</th></tr>
<tr><td>Clays and marly clays...</td><td>Deposits</td><td>Limestones, flinty limestones...</td><td>Marls, clay marls, and marly limestones</td><td>Sandstone, marly clays...</td><td>Shales and marls encompassing calcareous</td></tr>
<tr><th colspan="6">Slope</th></tr>
<tr><td>0–5</td><td colspan="2">5–15</td><td>15–25</td><td colspan="2">>25</td></tr>
<tr><th colspan="6">Exposure</th></tr>
<tr><td colspan="2">Flat</td><td>North</td><td>East</td><td>South</td><td>West</td></tr>
<tr><th colspan="6">Altitude</th></tr>
<tr><td colspan="2">0–500</td><td colspan="2">500–1000</td><td colspan="2">1000–2500</td></tr>
</table>

TWI, slope, exposure, and altitude, on the other hand, were classified on the basis of the reference literature on the subject [20,35]. Subsequently, these factors were processed using the chosen statistical method, WoE, while the main fire data were divided into two groups necessary to assess the reliability of the model created. The division between the two groups was performed by the SPSS 26 software (version 26) in a random manner for each year, respecting the relative percentages chosen. The first group was called the training group, as it helped form the model and corresponds to about 80% of the data, while there are two other groups that are needed to assess the reliability of the model: the first is the test group and corresponds to about 20% of the fire data (Figure 3); the second is another test group consisting of 20% of areas carefully selected so as not to intersect with any fires, areas shifted from the first test group, in order to test the model's ability to assign low susceptibility values to these areas as well, essentially to assess the model's ability to predict true negatives and false negatives (Figure 3).

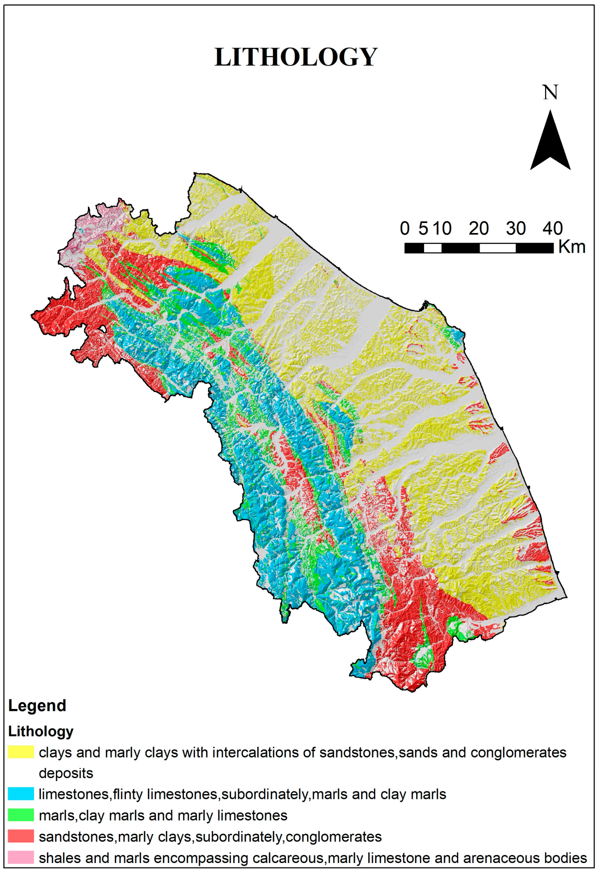

Figure 2. Lithology of the Marche region [34].

In order to predict the frequency of occurrence of an event in the territory, the WoE is based on the definition of weights calculated for each class of each variable on the training group, both positive weights, i.e., those that tend to increase the fire risk in this case, and negative weights, i.e., those that tend to decrease the fire risk for each class, are calculated [34].

$$W^+ = \ln\left(\frac{Wildfire\ area\ in\ class/Total\ wildfire\ area}{Fire - free\ area\ in\ class/Total\ fire - free\ area}\right) \quad (1)$$

$$W^- = \ln\left(\frac{Total\ wildfire\ area\ outside\ class/Total\ wildfire\ area}{Fire - free\ area\ outside\ class/Total\ fire - free\ area}\right) \quad (2)$$

The difference between W^+ and W^- makes it possible to calculate the contrast C and consequently to understand whether the factor considered has a positive weight that, therefore, increases the fire risk in that area or a negative weight that reduces it [34].

$$C = W^+ - W^- \quad (3)$$

where (C) = contrast.

The result of this statistical process was the wildfire susceptibility index (*WSI*), which is calculated as a summation of the contrasts of all factors considered, i.e., ecological units, TWI, geology, slope, exposure, and altitude in whatever order one wishes to consider ($C_{1st\ fac}$, ecc.) .

$$WSI_C = C_{1st\ fac} + C_{2nd\ fac} + C_{3rd\ fac} + C_{4th\ fac} + C_{5th\ fac} + C_{6th\ fac} \tag{4}$$

Finally, the model was validated, using about 20 per cent of the chosen sample as a test for the model, by analysing it with the ROC (receiver operating characteristic curve). In addition, to also test the model's ability to provide low susceptibility values for areas without fires, the same number and area of fires were selected for testing by moving the shapefile. ROC points represent pairs of false-positive (specificity) and true-positive (sensitivity) values, essentially studying the relationships between true alarms, in our case, areas that the model identifies as possible fire locations and actually are, and between false alarms, areas that the model identifies as fire-prone and actually are not.

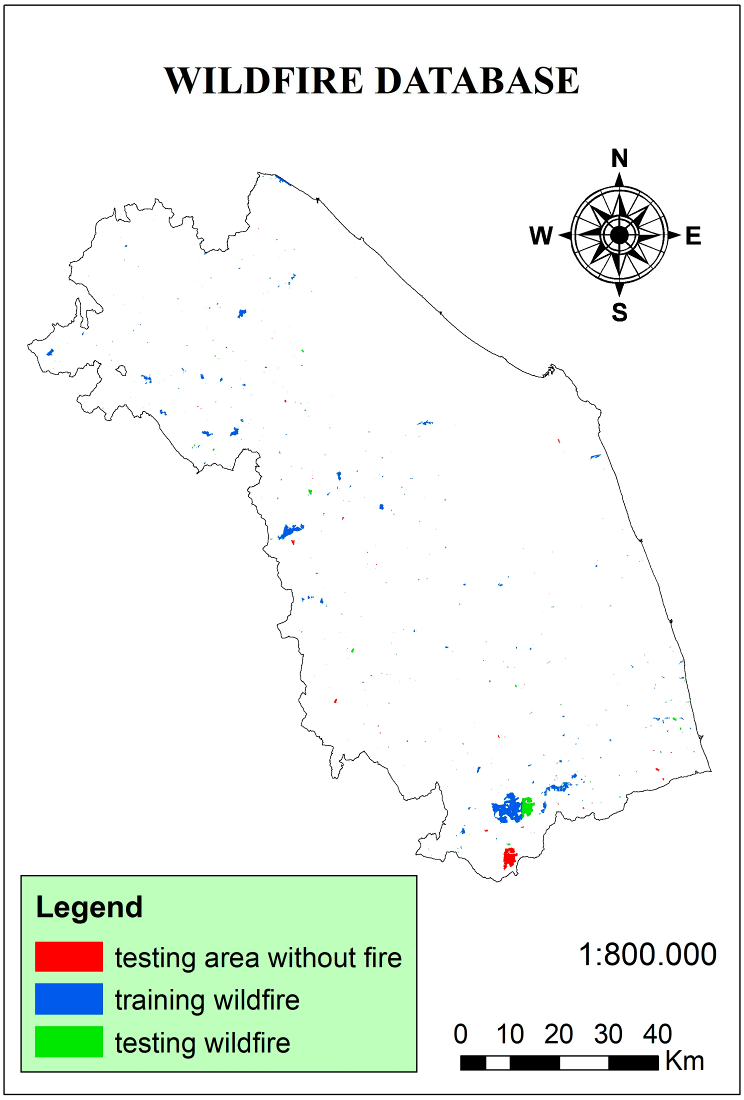

Figure 3. Wildfire database map with the division that was used for model training (training wildfire) and testing of both fire (testing wildfire) and fire-free areas (testing areas without fire). The testing part is not included in the processing of the model.

In relation to the occurrence of wildfires, sensitivity and specificity are calculated as follows:

$$y - axis,\ sensitivity = (TP/(TP + FN)) \tag{5}$$

TP = true positive

FN = false negative

whereas specificity is described by the following formula:

$$x - axis,\ specificity = (FP/(FP + TN)) \tag{6}$$

FP = false positive

TN = true negative

To give an unambiguous interpretation of the ROC curve obviously requires an invariant measurement with respect to scale, classification, and thresholds, which is the 'area under the curve' AUC method, a method that allows the measurement of the quality of the predictions of the model created. The AUC value is between 0 and 1, i.e., a model whose predictions are 100% wrong has an AUC of 0.0, and a model whose predictions are 100% correct has an AUC of 1.0. The AUC is, in fact, equivalent to the probability that the model result applied to an event randomly drawn from the fires is higher than that obtained by applying it to an event randomly drawn from the group of fire-free areas.

In order to interpret the AUC values, we referred to classifications already accepted in the scientific literature on the subject [34,36,37]:

- AUC = 0.5 the test is not informative;
- 0.5 < AUC $\leq$ 0.7 the test is inaccurate;
- 0.7 < AUC $\leq$ 0.9 the test is highly accurate;
- 0.9 < AUC < 1.0, the test is considered outstanding;
- AUC = 1 perfect test.

A logic diagram was drawn up to better understand the development of the study and its different phases (Figure 4).

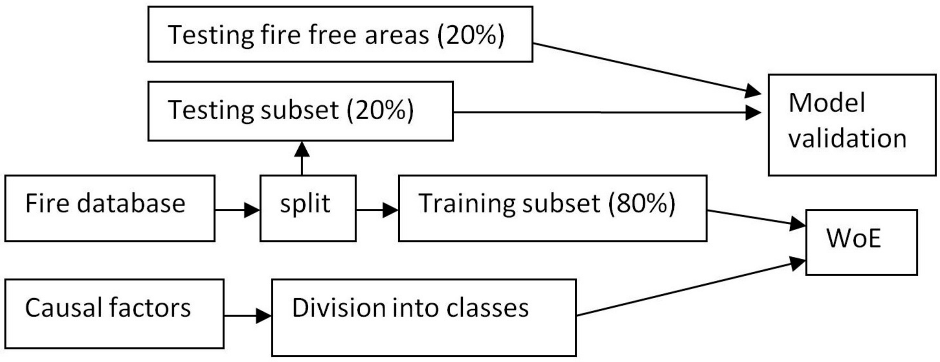

Figure 4. Model and validation diagram.

3. Results

3.1. WoE Factors

The six causal factors identified to develop the WoE model showed good results in discriminating between high and low fire risk areas, with contrast C values being quite revealing (Table 2).

Table 2. Contrast (C) and relative values for Formulas (1) and (2) for the classes considered within the individual factors. TF—total wildfire area; TNF—total fire-free area; TFoc—total wildfire area outside the class; TNFoc—total fire-free area outside the class; Fc—wildfire area in class; NFc—fire-free area in class.

Causal Factor	TF	TNF	Classes	C	TFoc	TNFoc	Fc	NFc
Ecological unit	12.9	9351.1	Airport	/	12.90	9351.04	0	0.06
			Deciduous shrubland	1.683	11.70	9172.92	1.204	178.18
			Evergreen shrubland	2.395	12.13	9297.21	0.770	53.89
			Bare area	−1.253	12.90	9346.78	0.002	4.32
			Roads	/	12.90	9350.56	0	0.54
			Mixed deciduous woodland	0.386	12.78	9292.62	0.118	58.48
			Hornbeam woodland	1.038	9.85	8326.80	3.054	1024.30
			Coniferous woodland	2.030	11.33	9181.68	1.569	169.42
			Riparian woodland	−0.620	12.75	9147.31	0.150	203.79
			Badland	/	12.90	9345.68	0	5.42
			Wood of chestnuts	−1.931	12.89	9303.16	0.010	47.94
			Quarry	/	12.90	9351.03	0	0.07
			Arboreal cultivation	−1.070	12.78	9096.07	0.120	255.03
			Continuous built-up area	/	12.90	8862.13	0	488.97
			Scattered built-up area	/	12.90	9220.84	0	130.26
			Beechwood	−1.791	12.85	9140.22	0.049	210.88
			Herbaceous heter. form.	/	12.90	9346.47	0	4.63
			Shores and beaches	/	12.90	9332.71	0	18.39
			Arboreal formation	/	12.90	9351.04	0	0.06
			Wasteland	2.924	12.89	9350.79	0.008	0.31
			Lake	/	12.90	9339.17	0	11.93
			Holm oak	−3.712	12.90	9308.26	0.001	42.84
			Poplar forest	/	12.90	9351.00	0	0.10
			Prairie	−0.310	12.35	8786.59	0.549	564.51
			Pre-forest	0.866	12.82	9325.64	0.083	25.46
			Decidual oak	0.981	10.34	8484.20	2.564	866.90
			Seedlet	−0.721	10.26	4409.03	2.644	4942.07
			Aquatic vegetation	/	12.90	9350.78	0	0.32
			Psammophilous vegetation	/	12.90	9351.01	0	0.09
			Riparian vegetation	/	12.90	9350.92	0	0.18
			Urban green	0.524	12.90	9349.79	0.003	1.31
TWI	12.9	9351.1	0–5	0.577	8.08	7009.21	4.82	2341.89
			5–10	−5.340	5.47	3035.85	7.43	6315.25
			10–15	−3.900	12.29	8694.35	0.61	656.75
			15–20	−3.498	12.86	9326.79	0.04	24.31
Geology	12.9	9351.1	Clays and marly clays...	−0.365	8.72	5005.24	4.18	4345.86
			Deposits	−0.764	12.81	9293.78	0.09	57.32
			Limestones, flinty limestones...	0.901	10.92	7574.97	1.98	1776.13
			Marls, clay marls, and marly limestones	−0.287	11.00	8169.25	1.90	1181.85
			Sandstone, marly clays...	0.074	12.15	8695.95	0.75	655.15
			Shales and marls encompassing calcareous	0.067	8.90	8029.23	4.00	1321.87
Slope	12.9	9351.1	0–5	−0.601	11.12	7240.03	1.78	2111.07
			5–15	−0.595	8.23	4612.18	4.67	4738.92
			15–25	0.702	8.99	7696.20	3.91	1654.90
			>25	0.916	10.36	8517.84	2.54	833.26
Exposure	12.9	9351.1	Flat	/	12.90	9346.64	0.00	4.46
			North	−0.245	10.00	6823.36	2.90	2527.74
			East	−0.403	10.22	6718.84	2.68	2632.26
			South	0.680	8.09	7189.43	4.81	2161.67
			West	−0.131	10.40	7339.07	2.50	2012.03
Altitude	12.9	9351.1	0–500	−0.644	4.58	2685.93	8.32	6665.17
			500–1000	0.501	8.53	7317.15	4.37	2033.95
			1000–2500	−1.587	12.69	8712.13	0.21	638.97

The first causal factor in Table 2 relates to ecological units, and here, broad discriminating factors are found between one unit and another; in particular, the evidence in the scientific literature on the subject is confirmed, with obviously different weights. High contrast values stand out for deciduous shrubland, evergreen shrubland, hornbeam woodland, coniferous woodland, wasteland, pre-forest, and deciduous oak, while the negative values, which therefore determine a lower propensity of the ecological unit to fire risk, are bare land, chestnut forest, arboreal cultivation, beechwood, and holm oak [38]. The TWI, which constitutes the second causal factor, shows substantial differences between the different values. In fact, as one might have assumed, positive contrast values are found for the class from 0 to 5, while it is very important for the exclusion of certain areas. In particular, contrast values greater than 5 for TWI are strongly negative, meaning that there is little likelihood that these areas will ignite a fire or at least not favour it. As far as geology is concerned, two classes are particularly important, one relating to deposits that have a negative weight, probably also due to their ability to absorb water, and the other relating to limestones that are rather predisposed to developing fires. It is likely that this predisposition of limestones to develop fires may be favoured by the forests that predominantly proliferate on this type of soil, such as hornbeam woodland and oak forests, which have a positive C [39]. The slope of the land is also evocative of a class-dependent differentiation; from 0 to 15% slope, the C-value is negative and thus tends to decrease the occurrence of fires, while above 15%, the C-value becomes positive and increases at higher slopes. Exposure also shows clear differences in fire ignition, showing that fire is much more likely to develop in south-facing areas while it is less likely to develop in east or north-facing areas. Finally, altitude is probably the least predictable causal factor, as the differentiated classes show negative C values in the 0–500 m and 1000–2500 m classes, while the positive values are in the 500–1000 m range. In this case, it is not easy to find the physical causes that lead to these results. However, it could be assumed that there are more forests in the 500–1000 m class than in the others, although it is certainly not the driest altitude class.

3.2. Wildfire Susceptibility and Model Validation

The classes of causal factors, which divided the study area into hundreds of thousands of polygons, were summed up on the basis of C. The result led to normalised values from 0 to 100 to obtain a wildfire susceptibility index based on the WoE statistical method. The wildfire susceptibility index (WSI) shows heterogeneous values, with the highest values concentrated mainly in the mountainous and hilly areas, which predominantly coincide with forested areas (Figure 5a). However, it is not possible, without adequate validation using the ROC (receiver operating characteristic) curve, to consider which areas are at a greater risk of fire outbreak and which are not. The analysis showed that values above 70 have a high level of fire susceptibility; therefore, according to the model, a fire is more likely to occur in those areas than in others with lower WSI values, which led to the need for an additional explanatory figure (Figure 5b).

In Figure 5b, only two values were used because the AUC procedure of the model validation highlights only 2 levels, one below WSI 80, where susceptibility is low, and the other above 80, where susceptibility is high. Therefore, we avoided creating other classes based on other values or averaging over intermediate values as we would have inserted a component of discretion into the analysis, making it statistically non-rigorous.

The validation carried out using the ROC curve led to fairly good results considering the absence of the purely climatic variables that usually, for all models, provide an added value to the reliability of the model. The AUC was obtained by testing the isolated sample, purposely studied, corresponding to about 20% of the fires that occurred; in addition, another 20% or so of areas corresponding to areas not subject to fire during the study period were selected by randomly moving the test file. This procedure allowed an accurate assessment of the model's reliability, which was 0.72 (AUC), and showed that some classes of WSI values were not present in the areas identified (Figure 6).

The AUC calculation using the ROC Curve was statistically significant, with a 95% confidence interval (alpha 0.05). A bar graph is also shown highlighting true positives, i.e., areas where the model indicates a high fire hazard and where fire has actually occurred. True negatives are the areas with no fires where the model attributes a low fire susceptibility, false positives are where the model indicates a high fire susceptibility and where the fire did not actually occur, and false negatives are where the model indicates a low fire susceptibility and where the fire actually occurred (Figure 7).

The model shows that the 6 identified geological, topographical and environmental causal factors can predict with 72% accuracy the areas that have a high possibility of developing a fire.

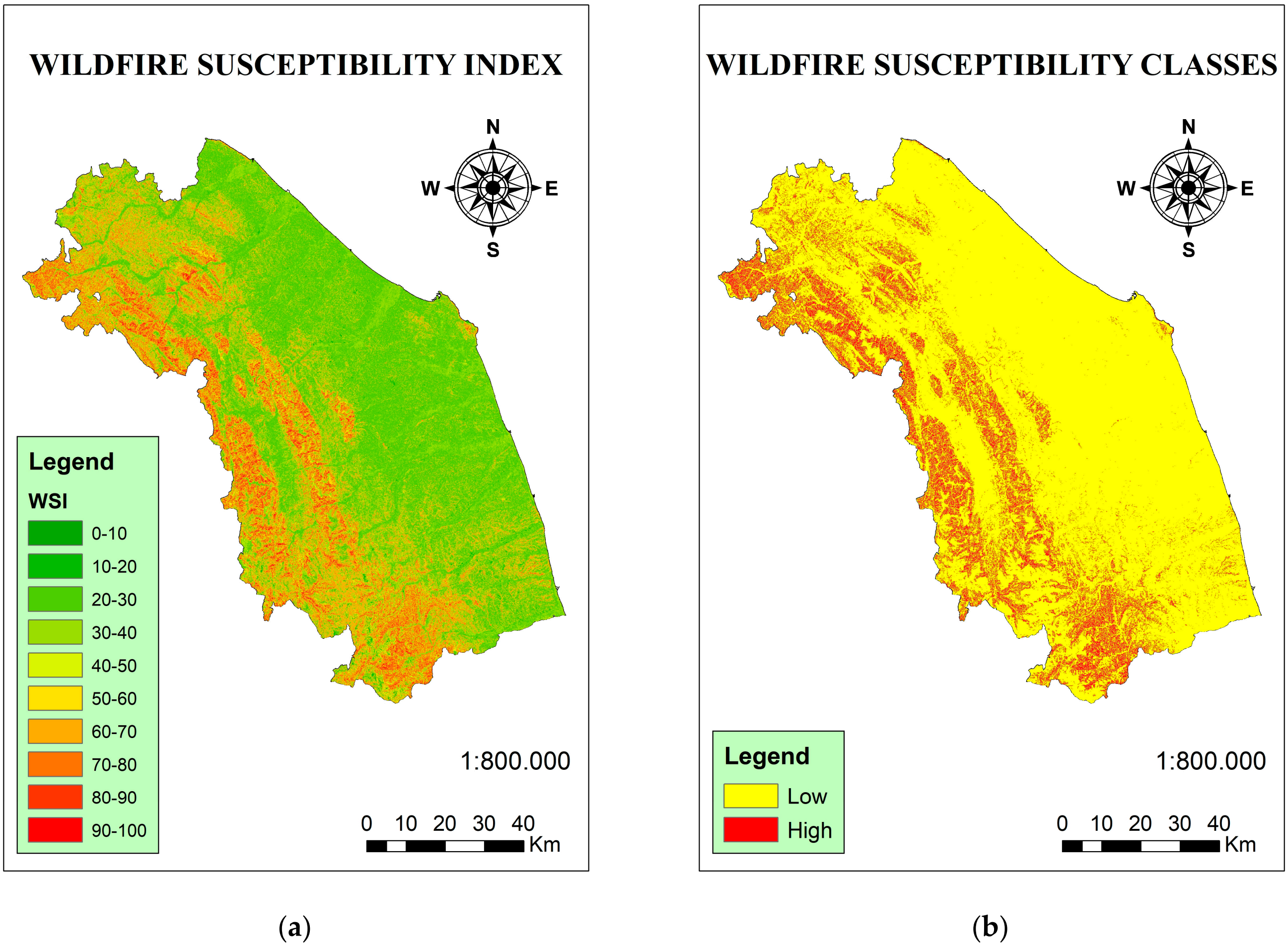

Figure 5. (**a**) Wildfire susceptibility index; (**b**) wildfire susceptibility classes.

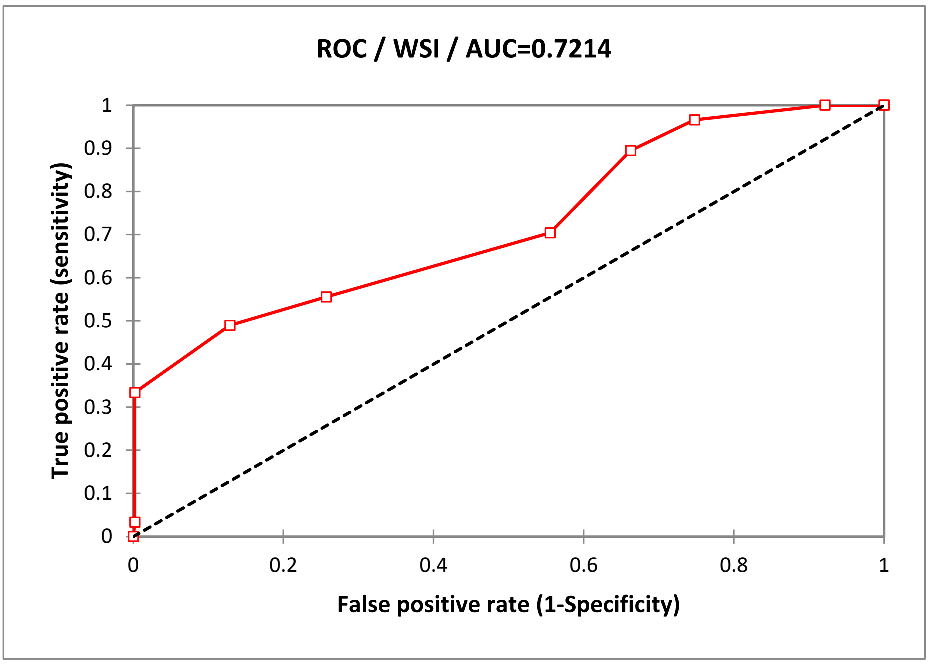

Figure 6. ROC curve for wildfire in the Marche region and AUC value.

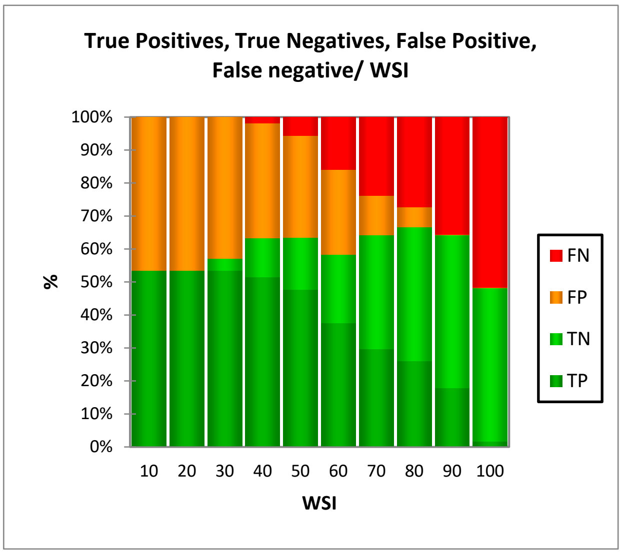

Figure 7. Case analysis for model validation. FN—false negative; FP—false positive; TN—true negative; TP—true positive.

4. Discussion

Fire susceptibility is an extremely important tool for spatial planning because it allows appropriate countermeasures to be taken in susceptible areas in order to limit possible ignition. In this research, fire susceptibility was assessed by choosing geological-topographical-environmental causal factors, with the intention of not taking into consideration the major activator of these processes, i.e., climate. This choice was made in order to assess the reliability of a fire susceptibility model not based on climatic causal factors and also because it could be useful to develop this model to define susceptibility in climatically under-sampled areas. The results were numerous, starting with the contrast that was observed for the individual causal factors, which showed how classes of values within the individual factors are more or less predisposed to the development of wildfires. The ecological units revealed highly differentiated contrast (C) values between the different classes, for example, the high C of coniferous forests, which are widely known in the literature to be very fire-prone [40]. The contrast was also high in the case of wastelands and shrublands, which, even in the most recent scientific research, are among the most fire-sensitive ecological units [41]. The research also highlighted ecological units that have the ability to reduce wildfire susceptibility, such as holm oak, which shows a highly negative C, in clear agreement with the scientific literature that even finds its fire-stopping properties [42]. The TWI, in turn, shows that areas where less moisture accumulates topographically are the most susceptible to fires, in this case in class 0 to 5, while the others having a negative C represent areas where fire development is less likely. The TWI has very variable values depending on the area where it is calculated, but even the scientific literature on the subject, regardless of the classes identified, agrees that a lower TWI corresponds to a greater fire hazard [43]. Geology, on the other hand, is rarely used in scientific research on fire susceptibility, and there are no unambiguous values, probably also due to the lack of lithological aggregation of individual geological formations, which was conducted in this study [44]. In any case, it was evident to consider that deposits, which retain more moisture than other geological formations, show a negative C, while limestones give rise to a positive C, probably also due to some tree species susceptible to fire, that are more predisposed to live in limestone soils. For slope and exposure, the results were in agreement with the latest research on the subject; in fact, there is the greatest susceptibility to fire when the area's exposure is to the south and the slope is over 15% [20]. Finally, with regard to altitude, the result showed a high C in the 500–1000 range, although it could be assumed that this is because it is the range with the greatest forest cover. However, the physical significance of this causal factor cannot be certain. As far as the result obtained with WoE is concerned, it is interesting because it was obtained without the climatic causal factors, which, on the other hand, are widely used in all research on this topic and are crucial for improving the analysis. The AUC obtained of 0.72 is certainly a good result considering not only the absence of climatic factors but also the heterogeneity and vastness of the area analysed. WoE is used extensively in the literature and often yields good results even in comparison with other statistical models for fire susceptibility assessment [45]. In relation to the causal factors used to build the model, there are no examples in the literature of fire susceptibility models where climatic factors have not been used, providing an innovative character to the present study [31].

5. Conclusions

The spatial analysis using GIS of the fires and the subdivision of the causal factors into classes made it possible to identify for each class the relative contrast value, which makes it possible to assess the positive or negative influence of the class considered in the development of fires. Among the classes of causal factors chosen, those that produce the most fires were identified as a southern exposure, slopes above 25%, the presence of limestone in the lithologies, and certain ecological units such as shrubland, coniferous woodland, wasteland, etc. The differentiation of the contrasts for the factors considered is in itself an increase in knowledge on the subject in the area. However, the subsequent merging into the model through the WoE method makes it a spatial planning tool, making it a reference point for analysis in climatically under-sampled areas. The future developments of this research can be very broad; in fact, they can be divided into two main strands, namely those related to improved detection of identified causal factors and those related to a broadening of causal factors. As far as the identified causal factors are concerned, surveys could certainly be carried out on an ever larger scale, e.g., in order to differentiate the ecological units even more accurately, but the same also applies to the geology of the area. On the other hand, with regard to the topographical variables, it would be interesting to reduce the cell size of the DEM used, introducing additional precision. With regard to the expansion of causal factors, it would be appropriate to supplement the model with additional factors, such as climatic factors at the level of indices that can assess the dryness of an area or through satellite surveys to obtain information on soil moisture. Average values or climate extremes could also be included, possibly selecting the periods when fires are most frequent in the study area. Finally, other statistical models could, of course, be tested to assess possible differences, comparing possible improvements in fire susceptibility predictions and in relation to the area under investigation.

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