Prescribed burning impact on forest soil properties–A Fuzzy Boolean Nets approach

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A B S T R A C T

The Portuguese northern forests are often and severely affected by wildfires during the Summer season. These occurrences significantly affect and negatively impact all ecosystems, namely soil, fauna and flora. In order to reduce the occurrences of natural wildfires, some measures to control the availability of fuel mass are regularly implemented. Those preventive actions concern mainly prescribed burnings and vegetation pruning.

This work reports on the impact of a prescribed burning on several forest soil properties, namely pH, soil moisture, organic matter content and iron content, by monitoring the soil self-recovery capabilities during a one year span. The experiments were carried out in soil cover over a natural site of Andaluzitic schist, in Gramelas, Caminha, Portugal, which was kept intact from prescribed burnings during a period of four years. Soil samples were collected from five plots at three different layers (0–3, 3–6 and 6–18) 1 day before prescribed fire and at regular intervals after the prescribed fire.

This paper presents an approach where Fuzzy Boolean Nets (FBN) and Fuzzy reasoning are used to extract qualitative knowledge regarding the effect of prescribed fire burning on soil properties. FBN were chosen due to the scarcity on available quantitative data.

The results showed that soil properties were affected by prescribed burning practice and were unable to recover their initial values after one year.

Keywords:
Prescribed burning
Forest soil
Soil physical properties
Fuzzy Boolean Nets
Fuzzy systems

1. Introduction

The Portuguese northern forests are often and severely affected by wildfires during the Summer season. These occurrences significantly affect and negatively impact all ecosystems, namely soil, fauna and flora. In order to reduce natural wildfires occurrence, some measures to control the availability of fuel mass are regularly implemented. Those preventive actions concern mainly prescribed burnings and vegetation pruning (PNDFCI, 2008; Neary et al., 1999). These actions have legal support under Portuguese law and generally are concentrated between October and April. In this context, the Portuguese Forestry Authority (AFN) programs these procedures regularly as several reports demonstrate their usefulness, since a direct relationship between the reduction of the combustible mass and the reduction of the number of wildfires in the Summer season has been shown (Botelho et al., 1999; Fernandes and Botelho, 2004).

Although it is generally accepted that soil temperatures are not significantly altered during the prescribed fire episode on forest area, as this is a relatively fast process, the same cannot be said about the loss of soil moisture and the physical and chemical characteristics of the soil (Anderson and Diniz, 2006; Carter and Foster, 2004).

In addition, it is also generally accepted that, in general, burning the vegetation enriches the superficial layer of the soil with most of the nutrients (Carter and Foster, 2004; Gonzalez-Perez et al., 2004). In fact, the destruction of the accumulated dry material contributes to modify the soil pH and the availability of nutrients in soil superficial layers immediately after the forest fire (Certini, 2005; DeBano, 1991; Neff et al., 2005; Rego, 1986; Vega, 2001). The non-volatilized material is deposited as ashes on the vegetationless soil surface.

However, research is still needed in order to determine the way in which soil responds to the prescribed forest fires, the impact in geosystems and the time it takes to reestablish the original properties of the soil (Rau et al., 2008).

The aim of the present paper is to model the effect of prescribed fire on some forest soil physical properties. The results presented in this work focus on a prescribed fire conducted in Gramelas–Caminha, Viana do Castelo district (NW Portugal) by

AFN in March 2008 with the intent of not only reducing the combustible mass associated with wildfire risk but also to control the infesting species *Hakea Sericea*.

Samples were taken during six different phases: before prescribed forest fire, right after the prescribed fire and 45, 90, 270 and 360 days after the prescribed forest fire, and were used to determine soil pH, soil moisture, organic matter and iron.

Gramelas is referred in the Portuguese cartographic unit as Ru 1,1. It has as pedological dominant units the thin umbric regosol in shale (RGul.x) and the umbric leptosol in shale (LPu.x). As subdominant pedological units, it has the chromic cambisol humic/umbric in deposits of quartzite and/or shales (CMux.vq), and the dystrict leptosol in shale (LPd.x) (DRAEDM, 1995; Serviços Geológicos de Portugal, 1961) Fig. 1.

According to the information available in the Portuguese soil map (DRAEDM, 1995; Serviços Geológicos de Portugal, 1961), this soil has the following characteristics: low capacity of cationic exchange, low degree of base saturation and low capacity of water and nutrient retention. It also possesses the following characteristics:

i) very reduced thermal amplitude;
ii) available conditions for the radicular development in the soil layer between 30 and 50 cm;
iii) low soil fertility;
iv) no occurrence of water in the soil throughout most of the year except in very short periods and during intense rainfalls;
v) occasional occurrence of a high deficit of water in the soil during July through September;
vi) high risk of erosion, without aptitude for agriculture and with low aptitude for the forest exploration and/or silvicul-ture–shepherd concerns;
vii) soil with less than 50% of coarse elements (rock and gravel) in horizons superficial and subsurface up to 50 cm of depth;
viii) without terraces or with wide terraces and
ix) dominant slopes varying between 25–30% and 40–45%.

The studied area (approximately 1 ha) had not been burned for approximately 7 years.

However, because of the variable terrain conditions and the uncertainty associated with external factors like weather conditions (for example, rain on the predicted day for data collection) or the process of sample collection (for example, finding rocks at the predicted collecting depth), and in order to obtain proper conclusions one would require many more samples and data, since standard statistical analysis would be unable to extract proper conclusions due to that variability and lack of a large volume of data. Obtaining so much data is expensive and labor intensive since it demands an abundance of manpower and equipment both in field work and laboratory analysis and equipment. Therefore, alternative solutions were needed to analyze the existing data. The use of fuzzy sets seemed appropriate since it was more important to obtain a qualitative measure of the variation of the fundamental soil chemical properties than a strict quantitative measure. Since the problem in question should be able to deal with sparse quantitative data and eventually expert knowledge, the option to use Fuzzy Boolean Nets (FBN) (Carvalho and Tomé, 2007; Tomé, 1998a, 1998b; Tomé et al., 2004) to extract qualitative information seemed a good alternative to solve the present problem.

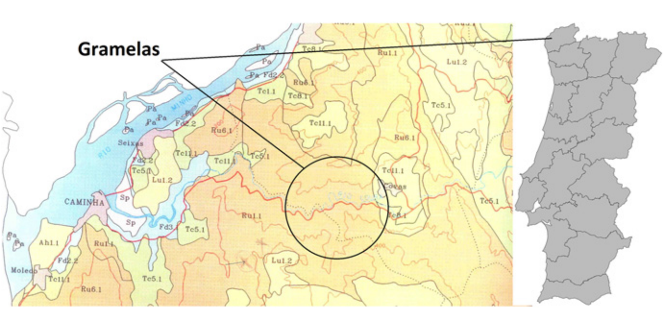

Fig. 1. Localization of the prescribed burnt area (official soil map of the region "Entre Douro e Minho", Valença sheet 1,2, on the scale of 1: 100 000.

2. Materials and methods

2.1. Sampling

The methods used to study fire impacts on soil were conducted according to the EUROFIELAB procedures (EUFIRELAB, 2006). The soil samples were collected in 5 distinct points: Point number 1 was located on a level land with low vegetation, close to a water line; Point number 2 was located in level land with lots of vegetation; Point number 3 was located on a strong slope with low vegetation, Point number 4 was located on a strong slope with lots of vegetation and Point number 5 was located on level land with low vegetation.

The sample collecting procedure was conducted according to the classic procedures adopted for forest soils. In this case, it was established under the scheme illustrated in Fig. 2. It consists of collecting 16 sub-samplings on a previously traced circumference with 2 m of diameter in three different depths (3, 6 and 18 cm).

The soil samples were collected using a clean manual auger and were transported to the laboratory in air-tight bags, which clearly identified the point of the sampling collection and the depth and the date of the collection procedure (before the prescribed forest fire, right after the prescribed fire and 30, 90, 270 or 360 days after the prescribed forest fire). For example, notation "1,18,30" indicates that the sample was collected at Point 1, at a depth of 6–18 cm and at 30 days after the prescribed forest fire.

Fig. 3 shows the appearance of the place labeled as Point 2 before, during and after the forest fire.

2.2. Laboratory procedures

The soil samples were prepared and submitted to analysis in a chemical analysis laboratory. Soil moisture and pH were determined according to Silva et al. (1975); the natural organic substance and iron according to Carter and Gregorich (2008). The results that were obtained are summarized in Table 1.

2.3. Fuzzy Boolean Nets

Natural or Biological neural systems have a certain number of features that lead to their learning capability when exposed to sets of experiments from the real world. They also have the capability to use the newly gained knowledge to perform approximate reasoning. Fuzzy Boolean Nets (FBN) (Tomé, 1998a, 1998b) were developed with the goal of exhibiting this kind of behavior. FBN can be considered a neural fuzzy model (Lin and Lee, 1996) where the fuzziness is an inherent emerging property, while in other known models, either fuzziness is artificially introduced on neural nets, or neural components are inserted on the fuzzy systems (Pedrycz and Gomide, 2007).

In FBN, neurons are grouped into areas. Each area can be associated with a given variable or concept. Meshes of weightless connections between antecedent neuron outputs and consequent neuron inputs are used to perform *If…Then* inference between areas. Neurons are binary, and the meshes are formed by individual random connections (just like in nature). Each neuron contains m inputs for each antecedent area, and a upper limit of $(m+1)^N$ internal unitary memories, where N is the number of antecedents. This number corresponds to maximum granularity (Pedrycz and Gomide, 2007), and can be reduced. It is considered that

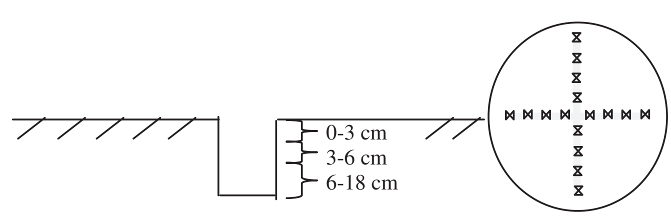

Fig. 2. The sampling collection scheme.

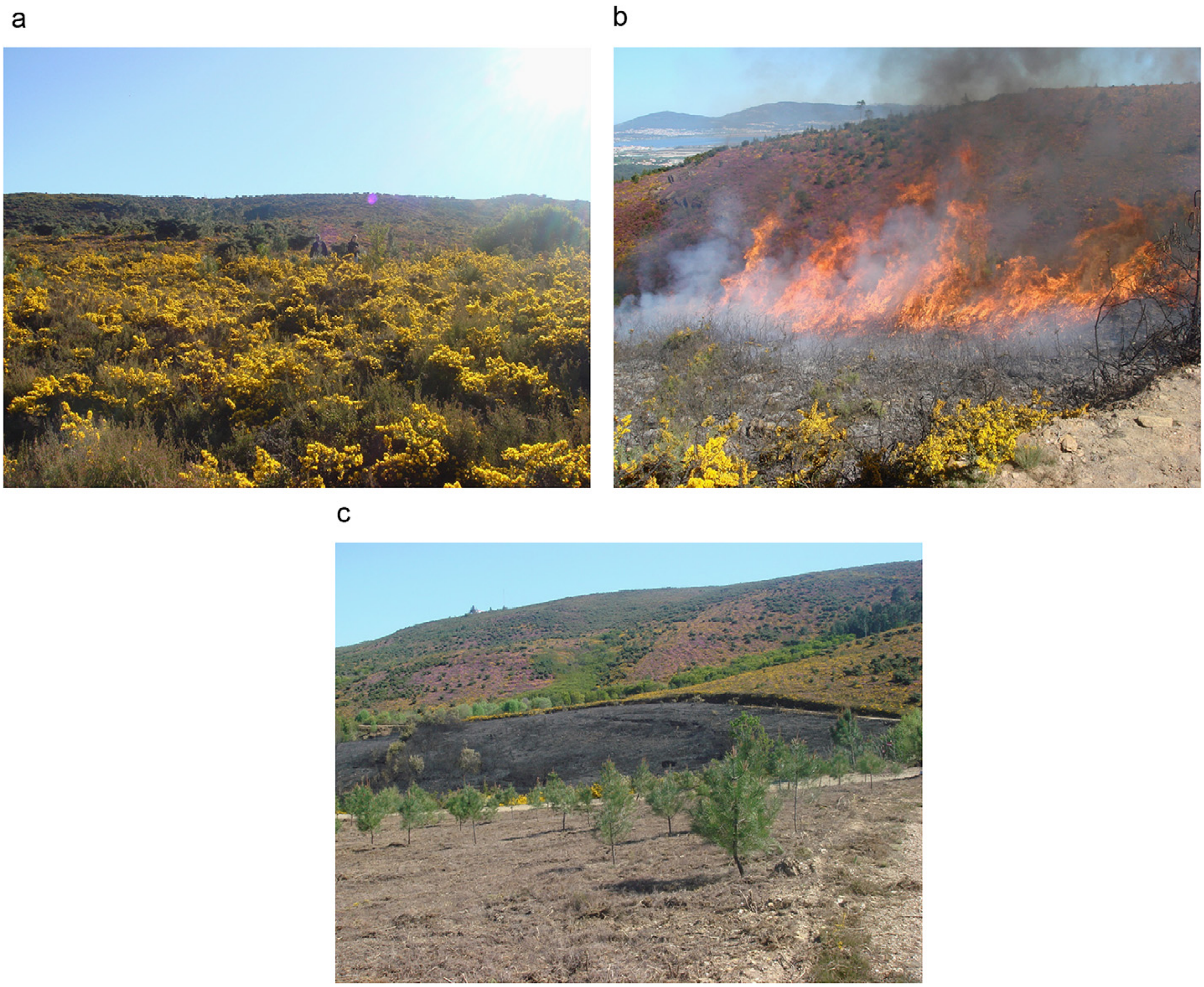

Fig. 3. Appearance of the area in study: (a) before, (b) during and (c) after the forest fire.

Table 1
Laboratory soil analysis results.

	pH						Soil moisture (%)						Iron content (g kg^{-1})						Organic matter (%)					
	pH 0	**pH 1**	**pH 30**	**pH 90**	**pH 270**	**pH 360**	**SM 0**	**SM 1**	**SM 30**	**SM 90**	**SM 270**	**SM 360**	**Fe 0**	**Fe 1**	**Fe 30**	**Fe 90**	**Fe 270**	**Fe 360**	**Om 0**	**Om 1**	**Om 30**	**Om 90**	**Om 270**	**Om 360**
1.3	5.4	6.7	6.4	7.0	4.6	4.3	42.3	26.9	45.8	39.6	29.6	19.5	12.3	24.7	37.7	42.7	24.5	13.9	3.3	0.9	11.5	17.1	7.3	12.4
1.6	4.9	6.3	6.2	6.7	4.5	4.3	41.7	14.5	42.1	42.5	27.5	21.2	18.8	41.6	72.7	44.9	15.9	13.7	6.2	1.0	9.8	21.0	6.8	8.9
1.18	4.9	6.4	5.9	7.5	4.5	4.2	44.7	18.4	49.4	44.9	28.5	24.0	20.3	21.1	48.4	47.4	19.4	14.3	9.5	1.2	18.4	34.8	7.4	8.7
2.3	5.8	6.5	6.4	6.9	4.6	4.2	27.8	23.6	34.6	14.9	25.5	15.3	11.7	20.7	41.0	19.7	19.2	15.8	16.0	7.4	21.7	23.4	12.6	13.7
2.6	5.5	6.4	6.1	5.9	4.4	4.1	21.0	19.6	26.2	18.3	21.3	19.9	12.8	37.6	22.3	17.6	18.7	16.3	19.0	7.9	20.1	26.1	4.9	11.3
2.18	5.4	6.3	6.0	6.2	4.2	4.0	21.1	18.2	22.6	17.9	24.4	26.3	22.8	27.1	39.9	28.2	17.4	16.5	46.3	7.2	15.5	18.8	5.7	9.0
3.3	4.9	6.5	6.2	7.7	4.6	4.2	25.6	24.8	31.5	14.4	37.9	17.2	20.7	45.7	30.6	24.6	17.2	20.8	19.9	9.1	17.4	23.2	13.4	10.7
3.6	4.9	6.2	6.1	7.4	4.6	4.1	20.1	24.1	26.8	15.2	30.7	20.5	18.6	27.2	41.7	22.7	24.9	21.8	16.7	9.7	13.8	17.9	9.2	11.8
3.18	4.8	6.1	5.7	6.7	4.4	4.1	16.2	24.9	24.5	26.0	30.0	22.7	38.5	42.9	25.0	39.1	21.5	21.3	18.6	8.9	21.9	21.0	5.4	8.5
4.3	4.9	6.1	5.9	8.3	4.5	4.2	29.6	25.1	34.9	19.8	45.6	12.7	35.0	23.7	21.2	17.3	20.2	19.2	18.7	10.9	26.1	32.0	14.4	12.3
4.6	5.9	6.2	5.8	7.1	4.5	4.1	22.6	32.6	29.6	24.4	39.6	17.9	24.9	44.2	23.8	27.6	18.5	19.3	19.9	11.4	24.1	18.2	6.6	9.4
4.18	5.9	5.9	5.6	7.7	4.5	4.0	19.9	29.4	27.4	21.4	36.3	19.7	27.8	30.0	28.6	27.3	19.4	19.8	18.8	10.7	16.0	27.2	6.2	11.4
5.3	5.8	6.8	5.8	7.4	4.4	4.0	20.7	14.0	24.5	12.1	33.7	27.1	20.8	41.1	29.6	32.5	13.7	14.9	9.9	0.1	22.3	19.1	13.8	11.9
5.6	5.7	6.3	5.3	6.6	4.6	4.0	22.3	16.4	26.7	16.1	26.7	28.9	31.3	23.5	25.3	25.9	13.6	15.2	11.2	0.1	18.1	22.4	4.2	13.8
5.18	5.8	6.0	5.4	6.2	4.6	4.0	14.6	18.1	21.8	16.4	28.4	29.9	35.0	40.8	30.6	22.1	15.1	14.9	10.3	0.1	15.7	18.6	8.2	13.3

each neuron's internal unitary memories can also have a third state with the "not taught" meaning. As in nature, the model is robust in the sense that it is immune to individual neuron or connection errors (which is not the case of other models, such as the classic artificial neural net) and presents good generalization capabilities.

The "value" of each concept, when stimulated, is given by the activation ratio of its associated area (which is given by the relation between active–output "1"—neurons and the total number of neurons).

Later developments use the "non-taught" state of FF, and an additional emotional layer (Tomé et al., 2004) to deal with validation, and solve dilemmas and conflicting information.

2.3.1. Inference

Inference proceeds in the following way: each consequent neuron samples each of the antecedent areas using its m inputs. Note that m is always much smaller than the number of neurons per area. For rules with N antecedents and a single consequent, each neuron has $N \times m$ inputs. In this particular case, rules have a single antecedent, therefore, each consequent neuron will have m inputs. The single operation carried out by each neuron is the combinatorial count of the number of activated inputs from every antecedent (in the single antecedent case, this operation is reduced in counting the active inputs). Neurons have a unitary memory (FF) for each possible count combination, and its value will be compared with the corresponding sampled value. If the FF corresponding to the sampled value of all antecedents contains a '1', then the neuron output will be '1' (the neuron will be – or remain – activated); if the FF is '0', then the neuron output will be '0'. These operations can all be performed with classic Boolean AND/OR. As a result of the inference process (which is parallel), each neuron will assume a binary value, and the inference result will be given by the neural activation ratio in the consequent area.

It has been shown (Tomé, 1998a) that, from these neuron micro-operations, emerge a macro-qualitative reasoning capability involving the concepts (fuzzy variables) (Pedrycz and Gomide, 2007), which can be expressed as rules of type:

"IF Antecedent1 is A1 AND Antecedent2 is A2 AND …THEN Consequent is Ci",

where *Antecedent1*, *Antecedent2*,.., *Antecedent2* are fuzzy variables and *A1*, *A2*; …, *Ci* are linguistic terms with binomial membership functions (such as, "small", "high", etc.).

2.3.2. Learning

Learning is performed by exposing the net to experiments and modifying the internal binary memories of each consequent neuron according to the activation of the m inputs (per antecedent) and the state of that consequent neuron. Each experiment will set or reset the individual neuron's binary memories. Since FBN operation is based on random input samples for each neuron, learning (and inference) is a probabilistic process. For each experiment, a different input configuration (defined by the input areas specific samples) is presented to each and every consequent neurons, and addresses one and only one of the internal binary memories of each individual neuron. Updating of each binary memory value depends on its selection (or not) and on the logic value of the consequent neuron. This may be considered as a Hebbian (Hebb, 1949) type of learning if pre- and post-synaptic activities are given by the activation ratios. A more detailed description of the learning process and proof that the network converges to a taught rule can be found in Tomé (1988a).

It has also been shown (Tomé and Carvalho, 2002) that an FBN is capable of learning a set of different rules without cross-influence between different rules, and that the number of distinct rules that the system can effectively distinguish (in terms of different consequent terms) increases with the square root of the number m.

Finally, it has been shown that an FBN is a universal approximator (Tomé, 1988a) since it theoretically implements a Parzen Window estimator (Parzen, 1962). This means that these networks are capable of implementing any possible multi-input single-output function of the type: $[0,1]^n \times [0,1]$.

These results give the theoretical background to establish the capability of these simple binary networks to perform qualitative reasoning and effective learning based on real experiments.

2.4. Using FBN and Fuzzy rule based inference to extract information on prescribed fire effects in soil properties

FBN was used to try to extract a complete linguistic relation that models how the analyzed parameters change after the prescribed fire. The linguistic rules describing the relation have the form of the following example:

"If Iron content is Low before prescribed fire, then it becomes Medium/High after d days"

In order to use FBN to extract information on prescribed fire effects in soil properties, the antecedent and consequent linguistic term set of the variables involved in the analysis must be properly defined *a-priori*: even knowing that FBN have the capability of automatically extracting linguistic membership functions from raw quantitative data, the scarcity of available data does not allows us to obtain an acceptable granularity. This restriction might be eliminated as more data become available, and the results compared with the present ones. Therefore, experts were contacted to establish linguistic terms to characterize the range of values in each analyzed parameter. Table 2 shows an example of the proposed range for the parameters pH, iron content and organic matter, and Fig. 4 shows an example of the membership functions used for pH linguistic terms.

All available raw data, which resulted from crisp uncertain measurements and/or observations, are used to train the FBN. Since the data set is not enough to provide a complete rule base, i.e., a rule for every available linguistic term, then the rule base must be necessarily completed before it can be used. FBN mesh based structure gives them a good generalization capability. Even small sized FBN can automatically interpolate values from large areas where training data were missing. For example, an FBN with 128 neurons per area, each with 25 inputs, can properly cover 20% of the input area for each provided crisp input results (Carvalho and Tomé, 2007). This is a theoretical limit, and in practice it is possible to obtain even better coverage. When using the proposed FBN settings, it is possible to obtain valid complete rule bases even with gaps up to 80%. This is obviously highly dependent on the nature of the problem we are dealing with, and for a gap that size, the fire effect on the analyzed component must be rather linear. In conclusion, such FBN can be used to complete any rule base for which 5 evenly spaced data points exist, obtaining a qualitative universal approximator as a result of the FBN inference. In the present case, since this is still a preliminary work, the number of data points is often smaller, so it cannot be guaranteed that the rule base is complete.

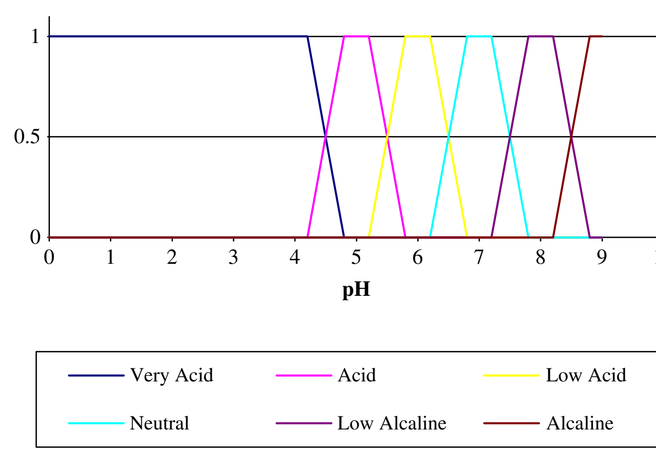

Fig. 4. pH linguistic terms and membership functions.

Table 2
Linguistic charaterization.

pH	PH value range	Iron content, organic matter	Iron content value range (g Kg^{-1})	Organic matter value range (%)
Very acid	< =4.5	Inexistant	0–4	0–2
Acid	4.6–5.5	Very low	4–10	3–8
Low acid	5.6–6.5	Low	11–20	9–18
Neutral	6.6–7.5	Medium	21–35	19–30
Low alkaline	7.6–8.5	High	36–65	31–45
Alkaline	8.6–9.5	Very high	66–1000	46–100

The procedure is as follows:

1. For each parameter at each sample depth, use an FBN with one antecedent associated with the pre-fire data, and one consequent area for each of the post-fire available data (days 0, 1, 45, 90, 270 and 360). Define 128 neurons per area with 25 inputs each and use maximum granularity. Although a larger FBN could provide a finer approximation degree, these settings provide a good compromise between computer performance and results,

2a. for each available expert rule obtain the centroid of the antecedent and consequent linguistic terms (x_i, z_k);

2b. for each available data point use the training data directly;

3. use all the points and all x_i, z_k as training data for the FBN. In such an FBN, twenty training epochs are sufficient to produce stable results;
4. after training completion, the FBN behaves as a qualitative approximator describing the effect of prescribed fire on the analyzed parameter in a large part of the UoD;
5. to obtain the consequent of a missing rule (C_j), one has to feed the FBN with the centroid of the antecedent linguistic term of that rule. Since FBN are probabilistic, one should infer the FBN several times and average the results to obtain z_j. The chosen consequent, C_j, will be the one where z_j has the highest membership degree; and
6. completion is guaranteed as long as at least 5 evenly distributed and reliable data points were available, but even with 3 evenly spaced rules/data points is possible to obtain good results (Carvalho and Tomé, 2007). Since FBN provides a way to verify the validity of a certain result (based on the ratio of taught/non-taught neurons that were used to infer the result), it is always possible to know how satisfactory the completion is (Tomé and Carvalho, 2004).

Whenever conflicting or incongruent data exist, one must use the FBN validation mechanisms and emotional layer to minimize their influence. Therefore, extra parameterization is required in this step, but the overall approach remains the same.

The outputs from the FBNetwork were also used to obtain a qualitative linguistic description of the effects of the prescribed fire in what concerns the variation of the analyzed soil properties. This was accomplished using a Mandani fuzzy rule based system (Pedrycz and Gomide, 2007) where several sets of simple fuzzy rules bases compare the pre-fire and post-fire linguistic terms given by the FBN. For example

"IF Iron content is Low before fire AND Iron content is Med after D_n days THEN Iron content Increased"

Table 3 shows the generic set of used rules. In the case of pH, the linguistic terms range from very acid to alkaline.

Note that the input values are obtained from the FBN output, which means that a continuous range of inputs if possible, e.g., a value can be anywhere between Med and High. The inference of these rules facilitated obtaining the conclusions presented in the following section.

3. Results and discussion

Since it was impossible to gather data to cover a complete range in all parameters (e.g., pH sampled values ranged only from acid to neutral), a complete model able to describe the impact of prescribed burning on forest soil properties was impracticable to obtain. However, by using FBN validation mechanisms to indicate where the model is providing acceptable results, it was possible to extract some qualitative knowledge regarding the effect of prescribed fire burning on soil properties.

For example, Table 4 shows the rules extracted for pH values at 3 cm depth. Areas in gray are deemed invalid by the FBN validation mechanisms, because there was not enough data to generalize the model in those linguistic values.

By inferring the FBNs on the valid ranges, and by applying the FBN outputs on the rule based system described in the previous section, it was possible to extract the following conclusions:

The soil pH values obtained before prescribed burning shows heterogeneity, varying from acid to low acid values in all locations and depth considered. Immediately after burning, soil pH values lost their heterogeneity and all values became closer to neutral. This soil status was not consistent and an increase in soil alkalinity in ensuing months was verified. This tendency was inverted 9 months after prescribed fire, where acidity levels increased again. One year after burning, it is possible to see that soil becomes much more acidic, and that all points and depths lost the original sampled heterogeneity. According to the results from our FBN model, the prescribed fire action on a forest soil tends to null its pH heterogeneity both in location and depth and clearly intensifies its acidity.

Regarding iron contents, this forest soil was quite heterogeneous before prescribed fire, with considerable variation in sampled values both in depth and location. Immediately after the prescribed burning a large increase in soil iron content was observed. However, this increase was only maintained for one month. One year after prescribed fire the soil iron content became, on average, lower to much lower than before burning. According to the results from our FBN model, the prescribed fire action on forest soils clearly causes depth homogenization and reduces iron content.

Soil organic matter is the parameter that shows the greatest variability in the analyzed soil. As obviously expected, the prescribed fire resulted in an immediate large to very large decrease in soil organic matter values, and in some plots values became almost null. Results from our FBN model did not allow us to obtain any relevant conclusions regarding the evolution of organic matter on subsequent sampling periods as this parameter shows no qualitative correlation with pre-burning values. However, it is possible to say that the prescribed fire clearly interfered on soil organic matter causing depth homogeneity.

Attempts were not performed to model soil moisture since it is significantly dependent on weather conditions. It is possible to associate the moisture increase 30 days after the fire and 45 days after the fire with the intense rainfall that have occurred.

Given the obtained results, we can assume that the prescribed fire (probably in conjunction with the heavily rainy season) had a

Table 4
pH (3 cm).

pH before burning	D0	D30	D90	D270	D360
Very acid	Acid	Low acid	Low acid	Low acid	Acid
Acid	Low acid	Low acid	Neutral	Acid	Very acid
Low acid	Low acid	Neutral	Low alkaline	Acid	Very acid
Neutral	Neutral	Neutral	Low alkaline	Acid	Very acid
Low alkaline	Neutral	Neutral	Neutral	Neutral	Acid
Alkaline	Neutral	Neutral	Neutral	Neutral	Neutral

Table 3
Qualitative variation of component after prescribed fire.

$D_0 \backslash D_n$	Inexistant	VL	Low	Med	High	VH
Inexistant	Maintain	Small increase	Increase	Large increase	VL increase	Huge increase
VL	Small decrease	Maintain	Small increase	Increase	Large increase	VL increase
Low	Decrease	Small decrease	Maintain	Small increase	Increase	Large increase
Med	Large decrease	Decrease	Small decrease	Maintain	Small increase	Increase
High	VL Decrease	Large decrease	Decrease	Small Decrease	Maintain	Small increase
VH	Huge decrease	VL Decrease	Large decrease	Decrease	Small Decrease	Maintain

significant impact on soils' parameters behavior, increasing its acidity, reducing its organic matter and iron content, and partially destroying soil heterogeneity in both depth and location. These conclusions are consistent to the approaches previously developed by Castro et al., (2009).

This is still obviously a qualitative interpretation approach based on very sparse data. Besides obtaining and analyzing more data from more diverse soils, future work will also include data from meteorological conditions linked to each season and related to sampling in order to complete and extend the model. It is also important to use some of the new data as a blind test set to validate the conclusions we have obtained so far, and to collect samples from non-burnt areas to use as a control data set.

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