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Research Article

Integrating fire risk considerations in forest management planning in Spain – a landscape level perspective

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Abstract

It is reasonable to assume that there is a relationship between the spatial distribution of forest fuels and fire hazards. Therefore, if fire risk is to be included into numerical forest planning, the spatial distribution of risky and non-risky forest stands should be taken into account. The present study combines a stand-level fire risk model and landscape level optimization to solve forest planning problems in which the fire risk plays an important role. The key point of the method was to calculate forest level fire resistance metrics from stand level indices and use these metrics as objective variables in numerical optimization. This study shows that maximizing different landscape metrics produces very different landscape configurations with respect to the spatial arrangement of resistant and risky stands. The landscapes obtained by maximizing different metrics were tested with a fire spread simulator. These tests suggested that the mean fire resistance of the landscape, which is a non-spatial metric, is the most important factor affecting the burned area. However, spatial landscape metrics that decrease the continuity of fire resistance in the landscape can significantly improve the fire resistance of the landscape when used as additional objective variables.

Introduction

In the countries of the Mediterranean basin, fire is the main cause of forest damage. About 50,000 fires sweep through an average of 500,000 hectares (1% of the forest area) of Mediterranean forest each year, causing enormous economic and ecological damage as well as loss of human life (Vélez 2002). In the Catalonia region (Spain), with an average of 12,000 hectares burned per year in the 1990s, forest fires are perceived by the public as the main environmental problem (Tábara 1996). The reduction in risk does not necessarily mean going back to total suppression policies (Finney and Cohen 2003). Instead, the risk of fire should be considered in ordinary silvicultural management and forest planning to find out efficient means to minimize fire damages cheaply.

Several authors have suggested fragmenting high-risk forest landscapes by using fuel breaks (Agee et al. 2000; Finney 2001; Hirsch et al. 2001; Finney and Cohen 2003). A fuel break may be created by thinning a strip of forest from below to reduce the amount of fuel, increase the height to crown base, and decrease crown closure. The fuel break may be under-burned. This kind of fuel break decreases the spread rate of fire and the overall fire risk (Finney 2001). Fuel breaks may convert a crown fire into surface fire (Agee et al. 2000), although fire can re-enter the crowns as it leaves the break (Loehle 2004). Loehle (2004) suggested that cellular percolation models be used to simulate fire-spreading patterns, providing insights into fire behavior and fire control strategies in general.

Since fire spreads in a specifically spatial manner, variables that measure the relative arrangement and connectivity of high/low risk forest stands as well as their total area are a way to affect the overall fire risk and safeness of a forest landscape. In this context, appropriate landscape metrics can make a major contribution (e.g. Palahí et al. 2004). Landscape metrics are variables that measure the sizes, shapes and connectivity of a certain kind of forest patches (McGarigal and Marks 1995). When dealing with the risk of fire, the landscape metrics should include the amount and location of forest stands that are fire sensitive or fire resistant. A number of landscape metrics can be formulated in order to influence the spatial arrangement of forest stands in relation to fire risk. Some landscape metrics require that the stands be classified into different fire risk types or, as high- and low-risk stands based on a threshold value.

Finding the optimal combination of stand management alternatives to maximize or minimize a landscape metric requires numerical optimization techniques. As most landscape metrics are spatial, the computational complexity of the planning problem calls for the use of heuristic search techniques (Borges et al. 2002; Pukkala 2002). These techniques are generally more flexible and more capable of addressing complicated objective functions and constraints than exact algorithms are (Reeves 1993; Borges et al. 2002).

The aim of this study was to illustrate and compare different landscape metrics in a planning situation where one of the management objectives was to reduce the risk of fire. González et al. (2005, unpublished) developed a stand-level model of fire risk applicable to forest management planning. The model predictors are measured in routine forest inventory or are easily calculated. The model was used to predict a fire resistance index for every management schedule of each stand. In the second step, various landscape metrics, computed from the fire resistance indices of stands, were included in optimization problems that were solved with heuristic methods. The resulting landscapes were tested with a spatial fire simulator that was developed for this purpose. All calculations except the fire simulations were done with a Spanish forest-planning system called Monte (Palahí 2002; Pukkala 2003), which was tailored for the analyses of this study.

Material and methods

The case forests

The study was conducted in two different artificial landscapes. Both represented forest conditions in the province of Tarragona in Catalonia (north-east Spain). The forest contained 900 square stands of 16 ha each distributed as a grid of 30 columns and 30 rows. The total area of the landscape was 14,400 ha. The artificial landscape was developed using real forest inventory data from the second Spanish National Forest Inventory (ICONA 1993). The adjacency information, which was required in spatial optimization, was generated for this setting. In the first forest (referred to as Tarragona Random) data of 900 plots from the National Forest Inventory in Tarragona were assigned to the grid cells randomly, resulting in a rather fragmented landscape. The mean growing stock volume of Tarragona Random was 27 m^3/ha. *Pinus halepensis* was the dominant tree species, followed by *P. nigra*, *Quercus ilex*, *P. sylvestris* and *Q. faginea*. The stand structures were closer to uneven-aged than even-aged structures.

The second forest (referred to as Uniform forest) was created by assigning the same stand characteristics to each of the 900 grid cells, thus creating a completely homogenous forest landscape. The forest consisted of uneven-aged *P. halepensis* 700 m a.s.l. with a volume of 48 m^3/ha and a rather high risk of fire.

Simulation of management alternatives

Alternative treatment schedules for the stands were simulated for a 30-year planning period, which was divided into three 10-year sub-periods. Both even- and uneven- aged management schedules were simulated. In the simulations of even-aged management, the stand was low-thinned once the stand basal area reached a 'thinning limit'. The stand was regenerated with the shelter tree method (Palahí and Pukkala 2003) when stand age exceeded the rotation age. To produce several alternative regimes for each stand, the rotation length was multiplied by 0.7, 1.0 and 1.3. With each rotation length, the basal area that activated the thinning (thinning limit) was multiplied by 0.5, 1.0 and 1.5. This produced nine different even-aged management instructions for the stand. In addition, nine different uneven-aged management instructions were generated by combining three cutting limits (basal area that activates the cutting) with three cutting intensities.

The individual tree models for *P. halepensis*, *P. sylvestris* and *P. nigra* developed by Trasobares et al. (2004a, b) were used to simulate stand development over the 30-year planning period. Unpublished but structurally similar models developed by Trasobares were used for the hardwoods present in the forest landscapes.

Stand-level model of fire risk

The risk of fire in a forest stand was predicted using the fire risk model developed by González et al. (2005, unpublished) for Catalonian tree species and stands:

$$\mathrm{FRI} = (1+\exp\{(-1.925-2.256\ln(\max\{Ele-7,1\}) -0.015Dg + 0.012G - 1.763P_{\mathrm{hard}} +2.081\left(\frac{SD}{Dg+0.01}\right)\})^{-1} \quad (1)$$

where FRI (Fire Risk Index), is the 12-year probability of the occurrence of fire in the stand. *Ele* is computed from:

$$Ele = \ln(\max\{\mathrm{Elevation} - 7, 1\}) \quad (2)$$

where Elevation is stand elevation above sea level (in hundreds of meters). Dg is the basal-area-weighted mean diameter (cm), G is the total basal area (m^2/ha), P_{hard} is the proportion of hardwood of the number of trees, and SD is the standard deviation of diameters at breast height (cm). The last predictor ($SD/(Dg + 0.01)$) expresses the variability of diameters in relation to the basal-area-weighted mean diameter. In stands with rather uneven structure the ratio is close to 1 and tends to be 0 in homogeneous stands. The model is based on all the inventory plots measured in Catalonia (10,855 plots in total) in the second national forest inventory of Spain, and 12-year post-inventory fire records for the same region.

The predictors of the fire risk model can be divided into three categories: variables describing stand density and structure (G, Dg and the ratio between SD and Dg), a variable describing the species composition (P_{hard}) and a variable describing the site (*Ele*). According to Equation (1), fire occurrence is highest between elevations 0 m and 700 m. Beyond 700 m it declines rapidly, the decline becoming more gradual at higher elevations. This relationship is consistent with another study (Schoenberg et al. 2003) and may be explained by fuel moisture, temperature, precipitation and population density. Forest stands with high values of G and SD/Dg have a high risk of fire, while stands with high values of P_{hard} and Dg have a low risk of fire.

The fire probability obtained from Equation (1) was converted to a fire resistance index so that a fire risk equal to or greater than 0.25 was considered to be equal to zero fire resistance (0.25 was the highest predicted 12-year risk of all National Forest Inventory plots of Catalonia) and a risk of zero was equal to resistance one. The conversion formula was as follows:

$$\mathrm{RES} = 4(0.25 - \mathrm{FRI}) \quad (3)$$

where RES is the fire resistance index of the stand. A threshold index was required for some of the landscape metrics tested in the study. In the absence of any true threshold value, a resistance index of 0.5 was used as a technical threshold. It corresponds to a 12-year fire probability of 0.125.

Landscape metrics

Six landscape metrics were analyzed as means of affecting the spatial distribution of fire resistance in the landscape: (1) Mean fire resistance; (2) Share of good–good boundary; (3) Share of good–bad boundary; (4) Mean difference; (5) Mean of neighborhood minima and (6) Mean of neighborhood maxima.

The mean fire resistance (MR) is the area-weighted mean of the resistance indices of stands. It is a non-spatial metric and gives reference for analyzing the remaining metrics, which are spatial.

The share of good–good boundary (G–G) refers to the configuration of low risk stands within the landscape. Stand boundaries are bisected into two groups, separating two similar or dissimilar stands, according to a threshold value of 0.5 of RES. Then, the proportion of good–good stand boundary (RES > 0.5 for both stands) of the total boundary length is calculated. The idea for using the share of good–good stand boundary is that when such a metric is maximized, low-risk stands tend to be connected, creating continuous breaks in the landscape that can act as fuel breaks. A high share of good–good boundary indicates a good connectivity of low risk stands within the landscape, which can result in reduction of the risk and the size of forest fires.

The share of good–bad stand boundary (G–B) refers to the percentage of a boundary between stands of high (RES > 0.5) and low (RES ≤ 0.5) fire resistance. The idea for using the share of good–bad stand boundary is to disconnect fire-risky stands, thereby increasing fragmentation with respect to fire risk.

The mean difference (MD) measures the average change in resistance at the compartment boundary, giving the overall dissimilarity of neighboring stands at the forest level. Maximizing the mean difference creates a forest landscape of maximally different neighbor stands with respect to their risk of fire resulting in a fragmented landscape with respect to fire risk. Compared to the G–B metric, MD does not use any threshold value for fire resistance.

The mean of neighborhood minima (MMin) is calculated as follows. First, every stand recives the lowest RES value of the stands in its neighborhood (RESmin). The neighborhood includes the stand itself and all other stands having common boundary with it. Second, calculation of the mean of the RESmin values of stands produces the MMin metric. The rationale behind this metric is that a risky stand (low resistance) makes all its neighbors also risky. When the metric is maximized, fire-risky stands will be placed so that they affect the other stands minimally. MMin reduces the amount and dispersion of high-risk stands (reducing potential ignition points).

The mean of neighborhood maxima (MMax) is calculated by first giving to each stand the resistance value of the most resistant stand of the neighborhood (RESmax, the stand itself is included in the neighborhood). Then the mean of the RESmax values of all stands in the forest is calculated. Maximizing the mean of neighborhood maxima creates a forest landscape where as many stands as possible will have at least one low-risk neighbor. The reason for using the MMax metric are the results obtained with percolation models (Loehle 2004). Percolation models have shown that treated stands (with low risk of fire), even if they are not directly connected, can have a good effect, acting as fuel breaks as well as protecting themselves (Loehle 2004).

Planning problems

Three different planning problems were formulated to test the landscape metrics in the two artificial case forests. The first type had one of the six landscape metrics as the sole objective variable. In this case, the objective function was simply:

$$\mathrm{Max}\,U = \mathrm{LM}_{l2034} \tag{4}$$

where U is the total utility and LM_{l2034} is the value of landscape metric l at the end of the planning period (in 2034).

The second planning problem had two objective variables: the volume of wood cut during the 30-year planning period, and a landscape metric:

$$\mathrm{Max}\,U = w_\mathrm{h} u_\mathrm{h}(\mathrm{H}) + w_\mathrm{l} u_\mathrm{l}(\mathrm{LM}_{l2034}) \tag{5}$$

where U is the total utility, w_h and w_l are, respectively, the weights of the harvested volume (H) and the landscape metric (LM), u_h is the sub-utility function for the total harvested volume, and u_l is the sub-utility function for landscape metric l. The weight of the production objective (harvest) was 0.6 (w_h) and the weight of the landscape metric was 0.4 (w_l). The sub-utility functions transform the absolute values of the variables measured in their own units to a relative sub-utility value (see, e.g., Pukkala 2002). The sub-utility function for the landscape metric was linear and determined through the smallest and largest possible value of the metric. The lowest possible value gave a sub-utility of zero and the highest possible value gave a sub-utility of one. The sub-utility function for harvest was determined by giving a priority of 1 to the target value and a priority of 0 for the minimum possible and maximum possible values. This created an ascending–descending function with the consequence that the cutting target was reached almost exactly. In the Tarragona Random Forest, the 30-year target cut was 500,000 m^3 and in the Uniform Forest 1000,000 m^3.

The third planning problem also had two objective variables: mean fire resistance in 2034 and a landscape metric at the end of the 30-year period (2034):

$$\mathrm{Max}\,U = w_{\mathrm{m}}u_{\mathrm{m}}(\mathrm{MR}) + w_{\mathrm{l}}u_{\mathrm{l}}(\mathrm{LM}_{t2034}) \qquad (6)$$

where MR is the mean fire resistance in 2034, w_{m} and u_{m} are, respectively, the weight and sub-utility function for the mean fire resistance. The target value of mean resistance was the mid-point of the range of variation, determined by the lowest possible and highest possible mean fire resistance in 2034. The target value was 0.544 for the Tarragona Random forest and 0.314 for the Uniform forest. A priority of 1 was given to the target value of mean fire resistance and a priority of 0 to both the smallest possible and the highest possible value. This ensured that exactly the target value was obtained. The sub-utility from the other landscape metric increased linearly as a function of the value of the metric.

The optimization problems were solved using the Hero (Pukkala and Kangas 1993) and tabu search (Glover and Laguna 1993) heuristics with one- or two-stand neighborhoods, depending on which method worked best in a particular problem (Heinonen and Pukkala 2004). In the Hero heuristic, 45 random searches were used to produce the initial solution. In tabu search the number of iterations was 2700, and 50 candidate moves per iteration were evaluated. The length of the tabu list was 27, which means that the most recent move was tabu for 27 iterations.

Evaluation of landscapes

A simple fire spread simulator was developed to evaluate the landscapes produced by maximizing different landscape metrics. In the simulation, strokes of lightning (or other source of ignition) hit random stands, which ignite fire with a probability equal to the predicted fire risk of the stand (Equation (1)). These stands are marked as burning stands, and they may spread fire to neighboring stands with the probability inversely proportional to the neighbor's resistance index (Equation (3)). After this, a burning stand becomes a burned stand and no longer spreads fire. The neighbors that catch fire may in turn spread fire to their non-burned and non-burning neighbors. The process stops when there are no burning stands left in the forest.

All solutions were tested with the fire-spread simulator. The simulation was done with one and ten strokes of lightning (attempted ignitions), and it was repeated 1000 times for every solution and both numbers of strokes. The mean burned area of 1000 simulations, expressed as the proportion of the burned area obtained when the mean resistance was the objective variable, was used to describe the fire resistance of the landscape.

Results

Landscape metric as the sole objective

The first set of problems, in which a landscape metric was the only objective variable, reveals the manner in which the tested metrics modify the landscape if the process is not hindered by other management goals. The results show that the tested metrics produced different landscapes (Table 1, Figure 1). The landscapes differed from each other in various ways. For example, maximization of good–good boundary (G–G) or good–bad boundary (G–B) in the Tarragona Random forest resulted in landscapes that differed considerably with respect to G–G and G–B but were fairly similar with respect to the other landscape metrics (Table 2). Comparison of the two forests reveals that the influence of the landscape metrics depends a lot on the initial landscape.

Maximizing the mean difference (MD) or the mean of neighborhood minima (MMin) produced landscapes that were very different in terms of many landscape metrics. In general, G–G and MMin as objective variables had rather similar effects on the landscape (Table 1, Figure 1). Both produced a smooth landscape with the fire-resistant stands aggregated and connected to each other, but the overall variation in resistance was clearly smaller when MMin was maximized. G–B and MD were also related objective variables and

Table 1. Values of landscape metrics in 2034 in the optimal plans for Tarragona Random and Uniform forest when one of the landscape metrics was the only objective variable.

Variable	Objective variable					
	MR	G–G	G–B	MD	MMin	MMax
Tarragona Random						
MR	**0.639**	0.586	0.530	0.524	0.621	0.550
G–G	60	**62**	18	18	61	24
G–B	34	32	**67**	65	32	52
MD	0.192	0.214	0.280	**0.362**	0.167	0.293
MMin	0.463	0.372	0.286	0.228	**0.472**	0.282
MMax	0.850	0.810	0.802	0.851	0.813	**0.861**
Uniform forest						
MR	**0.510**	0.510	0.351	0.313	0.510	0.302
G–G	100	**100**	0	1	100	8
G–B	0	0	**100**	94	0	49
MD	0.000	0.000	0.319	**0.369**	0.000	0.183
MMin	0.510	0.510	0.161	0.119	**0.510**	0.143
MMax	0.510	0.510	0.510	0.510	0.510	**0.510**

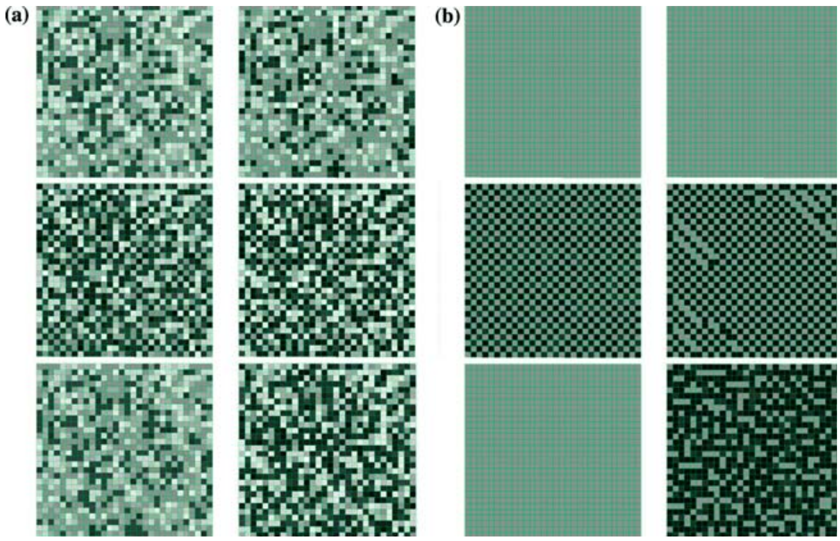

Figure 1. Value of fire resistance index in 2034 in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized. Dark tones imply low resistance. The maximized landscape metric is: top left, MR; top right, G–G; middle left, G–B; middle right, MD; bottom left, MMin; bottom right, MMax.

produced landscapes that look similar. The difference is that MD produced more variation in fire resistance than G–B did. Maximizing MMax produced landscapes different from all other landscapes in many respects, but the landscape was almost as highly fragmented as it was with the G–B and MD goals.

The landscape metrics used different types of cuttings to achieve the maximum value (Figure 2). Low thinning decreases the stand-level fire risk most, through the decrease in stand density and vertical diversity (reduced ladder effect), but it is also the most costly treatment (road-side price minus harvesting cost per cubic meter is high). Based on this rationale, G–B, MD and MMax may be cheaper to maximize than the remaining three metrics as they utilize less low thinning than do the other metrics.

Table 2. Values of landscape metrics in 2034 in the optimal plans for the Tarragona Random and Uniform forest when one of the landscape metrics was maximized with a 30-year cutting target of 500,000 m^3 (Tarragona Random) and 1000,000 m^3 (Uniform forest).

Variable	Objective variable					
	MR	G–G	G–B	MD	MMin	MMax
Tarragona Random						
MR	**0.601**	0.571	0.514	0.510	0.588	0.521
G–G	47	**61**	17	16	43	52
G–B	42	33	**67**	60	40	47
MD	0.206	0.222	0.294	**0.341**	0.178	0.305
MMin	0.406	0.342	0.260	0.224	**0.433**	0.247
MMax	0.824	0.804	0.798	0.837	0.797	**0.850**
Uniform forest						
MR	**0.458**	0.465	0.353	0.305	0.460	0.292
G–G	58	**73**	4	1	68	6
G–B	36	13	**87**	69	18	49
MD	0.020	0.030	0.271	**0.275**	0.009	0.189
MMin	0.339	0.419	0.166	0.137	**0.420**	0.139
MMax	0.510	0.496	0.510	0.492	0.502	**0.508**

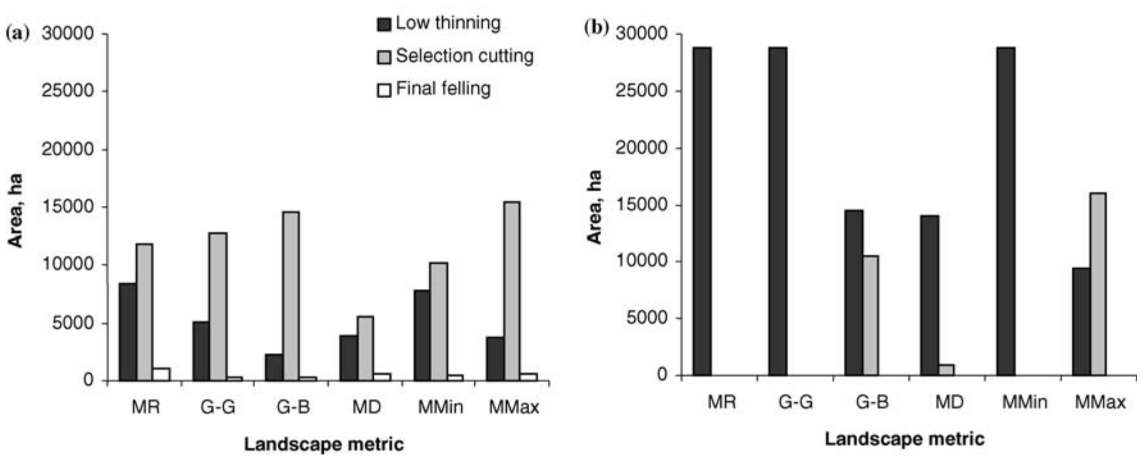

Figure 2. Areas of different types of cuttings in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized.

The average area that was burned in the fire simulations for the final landscape (year 2034) correlated closely with the mean resistance (Figure 3, Table 1). The burned area was very sensitive to the mean resistance. The results indicated that the spatial structure of landscape, in terms of fire resistance, is of secondary importance compared to the overall level of the resistance.

Landscape metrics with equal harvest

A more relevant problem setting for forestry practice is the second one in which a landscape metric was maximized with a certain cutting target. Results of these optimizations reveal how landscape metrics work if the forest also has production objectives. Equal cutting did not alter the overall picture of the behavior of the landscape metrics much. G–B and MD resembled each other (Table 2), but MD produced somewhat more variation in fire resistance than G–B did (Figure 4). G–G and MMin also had similar effects, but G–G produced more variation and MMin a smoother landscape. In many respects, MMax was between pairs (G–B)–MD and (G–G)–MMin. It produced a landscape in which there were corridors of both fire-risky stands and fire-resistant stands.

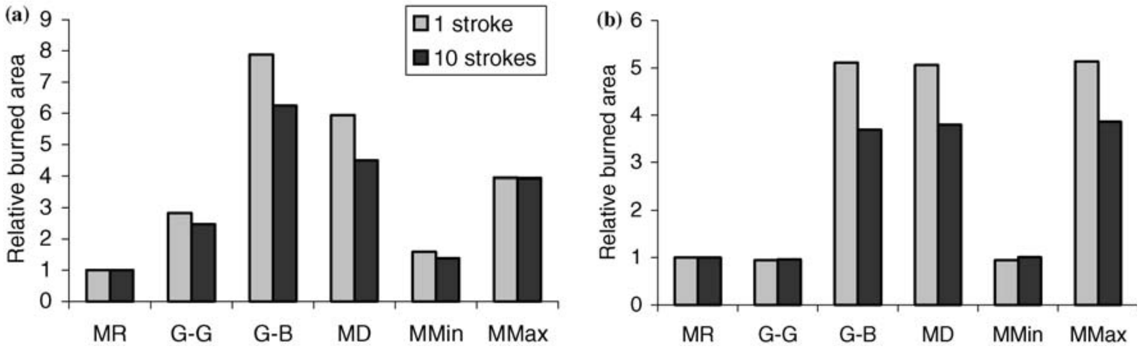

Figure 3. Relative burned areas in fire simulations with 1 and 10 strokes of lightning (attempted ignitions) in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized. The burned area when the mean resistance (MR) was maximized is set equal to one.

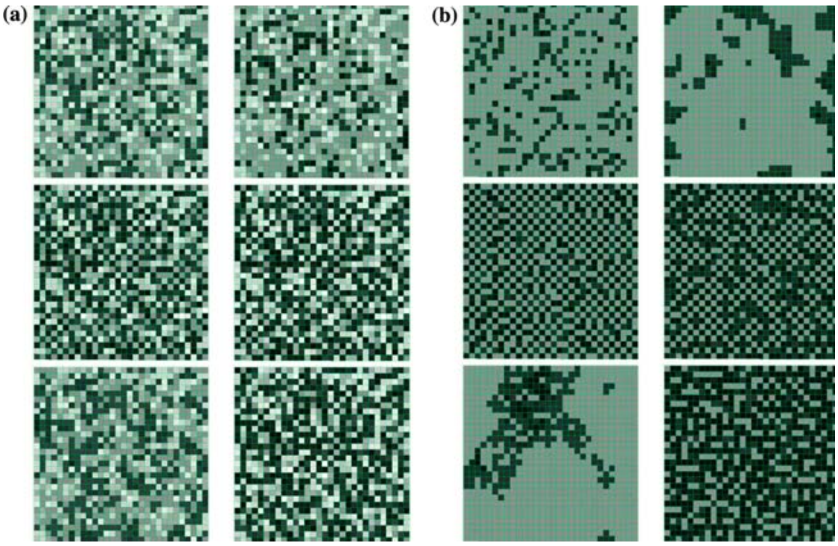

Figure 4. Value of fire resistance index in 2034 in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized with a cutting target of 500,000 m^3 (Tarragona Random) or 1000,000 m^3 (Uniform forest). Dark tones imply low resistance. The maximized landscape metric is: top left, MR; top right, G–G; middle left, G–B; middle right, MD; bottom left, MMin; bottom right, MMax.

All landscape metrics employed very few final fellings because new regeneration increases the fire risk of a stand (Figure 5). If the cost is measured with the area of low thinning, MD was the cheapest metric to be maximized in the Tarragona Random Forest and MMax in the Uniform Forest. MR, G–G and MMin employed twice as much low thinning as G–B, MD and MMax.

Those landscape metrics that produced the highest mean resistance had the smallest burned area in the fire simulations (Figure 6, Table 2). In this respect, the results were similar as in the first problem, but because all solutions now had the same total harvest, the relative differences in burned area were smaller.

Landscape metrics with equal mean fire resistance

The last set of optimizations shows the spatial effects of landscape metrics when variation in the overall resistance level is eliminated. The mean fire resistance of the landscape in 2034 was forced to be the same in all solutions for a forest landscape. In the optimizations for MR the spatial configuration of the landscape is largely random; many

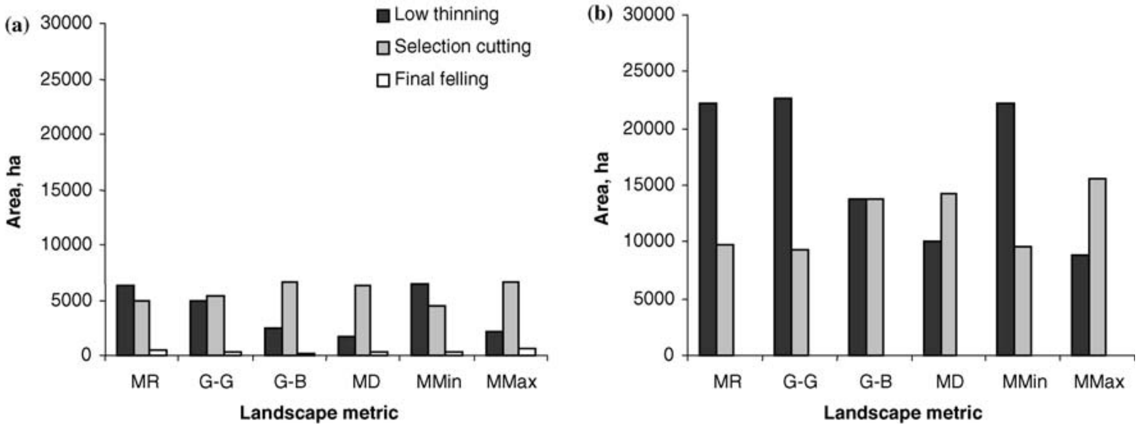

Figure 5. Areas of different types of cuttings in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized with a cutting target of 500,000 m^3 (Tarragona Random) or 1000, 000 m^3 (Uniform forest).

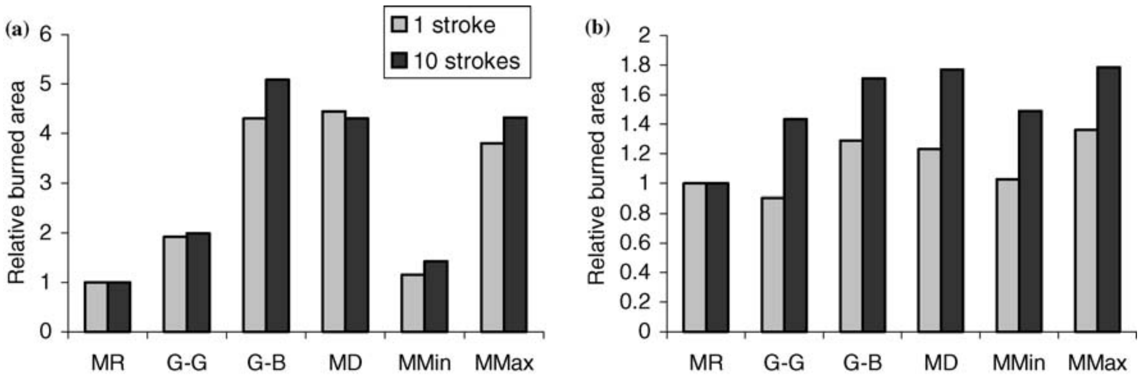

Figure 6. Relative burned areas in fire simulations with 1 and 10 strokes of lightning (attempted ignitions) in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized with a cutting target of 500,000 m^3 (Tarragona Random) or 1000, 000 m^3 (Uniform forest).

different spatial distributions had produced the same MR.

These optimizations also support earlier conclusions about the similarity and dissimilarity of the effects of landscape metrics (Table 3). However, G–B and MMin now had more different effects on the landscape than in previous problems: G–G produced and aggregated stands with fire resistance just above 0.5, and the remaining stands were very fire risky (Figure 7). When MMin was maximized, there were fewer low-resistance stands and they were as far as possible from the resistant stands. G–B and MD had rather similar impacts on the landscape, and MMax differed from all other metrics.

In the Uniform Forest, none of the landscape metrics used final felling (Figure 8). In Tarragona Random, several of the metrics were rather similar in terms of the areas of cuttings (Figure 8a), but the resulting landscapes differed substantially (Figure 7a). In the Uniform Forest, the cutting strategies employed by different metrics were drastically different. For example, MMin used much selection felling and few low thinning, while G–G, G–B and MD used more low thinning than selection felling. With all landscape metrics the low-thinning areas were fairly similar, suggesting that when the primary management objective is to achieve a certain mean fire resistance, there may not be large differences in the costs of maximizing different spatial landscape metrics as a secondary objective.

Some of the landscape metrics now produced burned areas clearly smaller than obtained with a

Table 3. Values of landscape metrics in 2034 in the optimal plans for the Tarragona Random and Uniform forest when one of the landscape metrics was maximized with a mean fire resistance (MR) target in 2034 of 0.544 (Tarragona Random) or 0.314 (Uniform forest).

Variable	Objective variable					
	MR	G–G	G–B	MD	MMin	MMax
Tarragona Random						
G–G	60	**61**	19	23	21	22
G–B	32	31	**66**	62	41	51
MD	0.226	0.223	0.272	**0.347**	0.179	0.289
MMin	0.313	0.315	0.307	0.242	**0.405**	0.281
MMax	0.786	0.784	0.812	0.853	0.771	**0.859**
Uniform forest						
G–G	18	**41**	3	4	21	12
G–B	25	8	**89**	87	10	51
MD	0.110	0.053	0.336	**0.342**	0.033	0.189
MMin	0.195	0.259	0.125	0.120	**0.286**	0.143
MMax	0.427	0.387	0.510	0.510	0.357	**0.510**

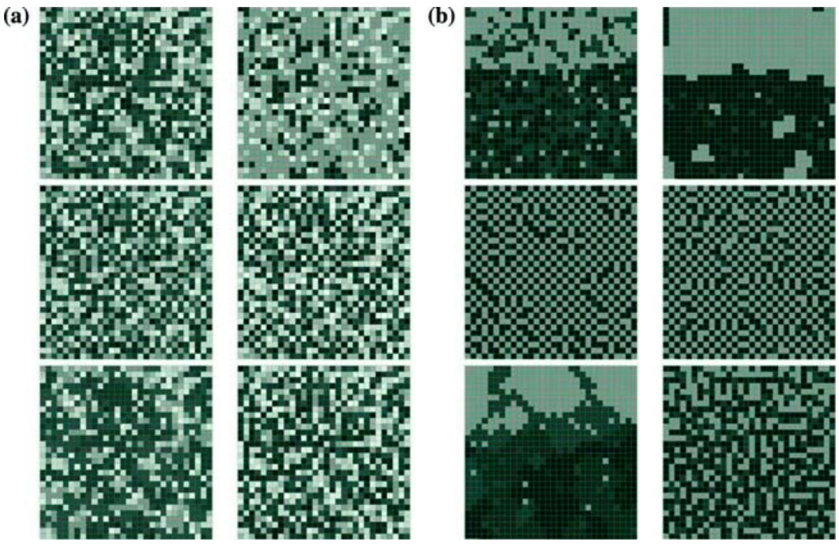

Figure 7. Value of fire resistance index in 2034 in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized with a mean resistance target of 0.544 (Tarragona Random) or 0.314 (Uniform forest) in 2034. Dark tones imply low resistance. The maximized landscape metric is: top left, MR; top right, G–G; middle left, G–B; middle right, MD; bottom left, MMin; bottom right, MMax.

fixed target resistance but without a spatial goal (Figure 9). In Tarragona Random, those landscape metrics that most increased fragmentation and created discontinuities at compartment boundaries, namely G–B, MD, and MMax, produced landscapes in which the simulated burned area was up to 40% lower than without the spatial goal. The differences are statistically significant (except MR vs. MMax with 10 strokes), because the 95% confidence limits, calculated from 1000 simulations for G–B, MD and MMax, did not overlap with the confidence limits of MR. The relative differences were greater with 1-stroke simulations, which is logical as simulations with several strokes create ignition points in different parts of the landscape, decreasing the effect of fuel breaks and the spatial structure of the landscape.

Discussion

The stand level offers the first meaningful level for evaluating the fire risk of a forest. Stand-level

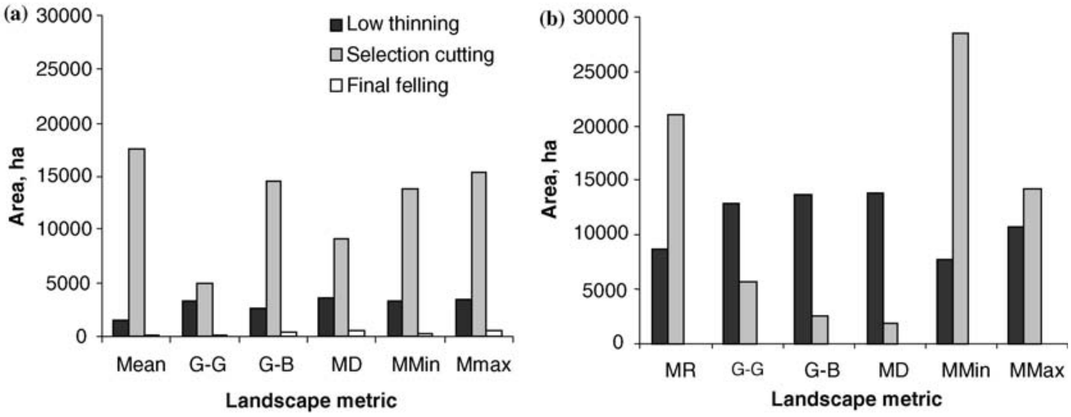

Figure 8. Areas of different types of cuttings in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized with a mean resistance target of 0.544 (Tarragona Random) or 0.314 (Uniform forest) in 2034.

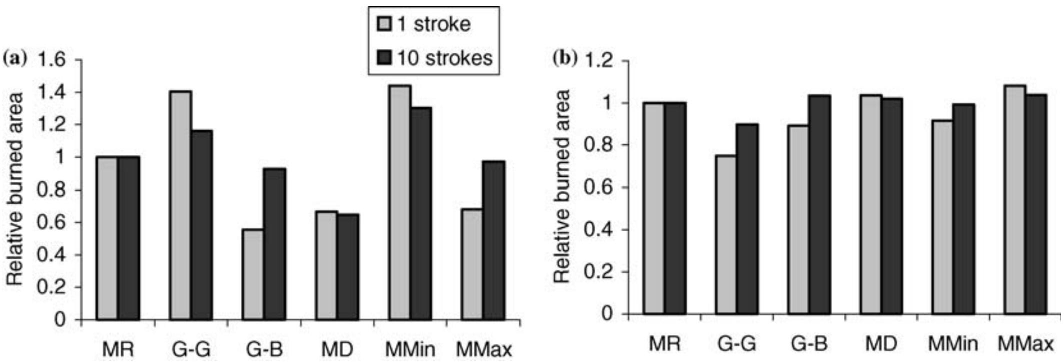

Figure 9. Relative burned areas in fire simulations with 1 and 10 strokes of lightning (attempted ignitions) in Tarragona Random (a) and Uniform forest (b) when one of the landscape metrics was maximized with a mean resistance target of 0.544 (Tarragona Random) or 0.314 (Uniform forest) in 2034.

models of fire risk, like the one developed by González et al. (2005, unpublished), predict the effect of stand structure and silvicultural operations on the degree of fire risk in a stand. Combinatorial techniques of optimization can be used to affect the composition and structure of the entire landscape with respect to fire risk. Treating all stands for minimizing fire risk might be too costly and not feasible. As fire spreads in a spatial manner (Loehle 2004), the spatial layout of both low-risk stands (fuel breaks) and high-risk stands is significant. Landscape metrics measuring the relative arrangement and connectivity of different types of forest stands with respect to fire risk, can play a major role in integrating fire risk considerations in forest planning and in addressing the problem at the landscape level.

The approach developed in this study simplifies the reality in a few respects. The model used to predict stand-level fire resistance used elevation as the only predictor in addition to growing stock characteristics. Elevation correlates with fuel moisture, temperature, rainfall and population density, which means that, to some extent, the model describes the influence of meteorological and anthropogenic factors on the risk of fire.

However, the model ignores slope and aspect because they were no statistically significant predictors of the stand-level probability of fire.

The landscape metrics used to affect the spatial distribution of fire resistance may not be the best possible. If it is important to place the fuel breaks in some critical places (Finney and Cohen 2003), it might be worthwhile to use a location-weighted mean resistance as the objective variable. If the main wind direction or the aspect of the slope is of importance, it is possible to use difference in elevation or the direction of the neighbor as a weight when calculating the MD, G–G or G–B the statistics. This would enhance the formation of fuel breaks that are perpendicular to the main wind direction (Finney 2001) of parallel to contour lines.

Also the fire-spread simulator that was used to compare the landscape metrics was a simplification as it ignored important factors such as wind, topography and weather conditions (fuel moisture). However, all these factors could be easily incorporated in the simulator by making the probability of spreading dependent on the directional distribution of wind, slope, aspect, etc. Varying weather conditions could be mimicked with stochastic multipliers for ignition probability and the probability of fire to spread to neighbor stands. However, since the purpose of the fire simulations was to compare the relative merits of different landscapes rather than to predict exact burned areas, these refinements were considered unnecessary.

This study showed that a forest landscape can be configured in very different ways with the help of landscape metrics, even when the harvest level or the mean fire-resistance is fixed. According to the results obtained, maximizing the mean of neighborhood minima (MMin) produced the smoothest and least fragmented landscape with respect to fore resistance. Since many stand features are strongly correlated, the landscape is most probably non-fragmented also in other respects such as habitat quality of flora and fauna, opposite to, G–B, MD and MMax, for instance, which will probably lead to severe habitat fragmentation.

Maximizing the MD metric produced the most differences at stand boundary, meaning that fire resistance changes maximally when one moves in the forest and crosses stand boundaries. Maximizing MMax produced corridors of non-risky stands, i.e. continuous fuel breaks, but also corridors of risky stands, i.e. pathways for fire. The G–G metric tended to join resistant stands and, as a result, disconnect risky areas, which should be a good feature for fire management. However, the difference in fire risk between fuel-break and non-break areas may be small since the bisection of stands into good and bad areas is based on a single threshold.

Of the six landscape metrics tested, G–B and MD differ from the other metrics so that both low- and high-risk stands are required to maximize the metric, whereas for high MR, G–G, MMin and MMax only low-risk fire resistant stands are needed. For a high MMax, it is enough that every stand has one resistant neighbor, and the resistance value of most stands is irrelevant. This difference between groups of metrics is clearly visible in Table 1 and Figure 2b, which show that indices to which risky stands do not contribute or which are not indifferent to a certain percentage of risky stands produce the highest mean resistance (Table 2) and employ much risk-reducing silvicultural operations (Figure 2b). Taking these facts into account, it is logical to use MR, G–G or MMin if only one fire-related objective variable can be included in the optimization problem, and management cost is not important. However, it is quite evident that a combination of two or more metrics produces a better landscape than a single metric alone. The results suggest that the mean fire resistance should always be an objective variable, but the use of one or several additional metrics may further improve the solution. Maximizing for instance good–good boundary (G–G) and simultaneously minimizing good–bad boundary (G–B) as an additional objective should produce a landscape with connected fuel breaks and few ignition areas.

Those indices that fragment the landscape most apparently are the cheapest to maximize. In the problem formulations of this study, however, the management cost was not actually minimized, but was calculated afterwards for solutions that aimed at other objectives. The cost was not measured in terms on monetary expenses but with the total area of low thinning. Therefore the conclusions about cost effectiveness of different metrics are preliminary. A thorough economic analysis of the fire-management alternatives should also take into account the effect of fire risk on the expected income from timber sales.

The fire simulations suggest that the spatial layout of the landscape is of small importance compared to the overall level of fire resistance (Keeley and Fotheringham 2001). However, the conclusion will change if the results are viewed from a different perspective and it is analyzed how good a landscape metric is with a given mean resistance. Figure 10 was compiled from the optimization results to illustrate this perspective. It shows that in Tarragona Random, MD, G–B, and MMax result in burned areas clearly smaller than obtained with the same mean resistance but without spatial goals (Figure 10a). The benefit of using spatial goals decreases when the number of ignition points increases (Figure 10b), which is logical.

In Tarragona Random, those metrics that produced the smoothest landscape (G–G and MMin) with a fixed mean resistance, were the worst in fire simulations (Figure 9a). This and the good performance of G–B and MD metrics suggest that increasing fuel fragmentation is good for fire management (Minnich 2001). However, an opposite result was obtained for the Uniform forest, where G–G and MMin gave the smallest burned area when the mean resistance was fixed (Figure 9b). The difference can be explained by the differences between the two forests; in the Uniform forest the highest possible resistance in 2034 was 0.510, which is a rather low value and only slightly higher than the threshold bisecting good and bad stands. This means that the fuel breaks created by the landscape metrics (e.g. corridors of good–good stands) were not very efficient in the Uniform forest with a consequence that wider low risk areas, i.e. a smoother landscape, is required to extinguish fire.

The fire simulations also indicate that the fire resistance of a 'break area' must be high to make it efficient. Also the rather poor performance of the G–G metric suggests that the threshold that makes a stand good (fire resistant) should be clearly higher than 0.5, which was used in this study. Resistant enough areas may not be obtained with ordinary silvicultural treatments in all forests. An example is our Uniform forest, which consisted of a single fire-prone species of small average tree size. Most probably the results for this forest had been better if special fire-management treatments had been simulated for the stands, like clear-cutting without planting, very heavy low thinning, and planting of hardwood. With these kinds of additional treatment options for stands, the optimization would most probably have been able to generate more fire-resistance landscapes than found in this study. However, as such special treatments may be costly, it is important to include the cost or production loss in the optimization to find low-risk but cheap solutions.

Conclusions

The study showed that if individual stands can be managed in several alternative ways with respect

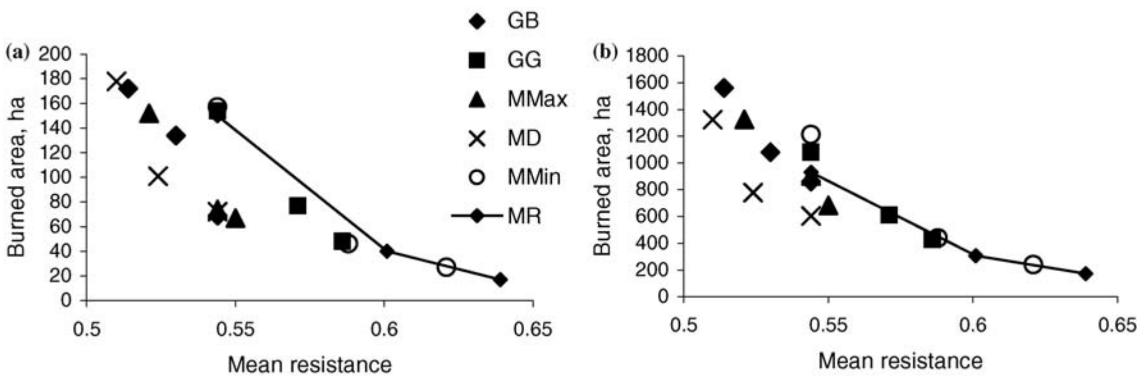

Figure 10. The mean burned area in Tarragona Random in fire simulations with 1 (a) and 10 (b) strokes of lightning (attempted ignitions) when one of the landscape metrics was maximized either alone or together with another objective variable (harvested volume of mean resistance). The symbol indicates the landscape metric that was maximized. Solutions obtained without spatial landscape metrics are connected with lines (the mean resistance has been the only fire-related objective variable).

to fire resistance, the use of spatial objective variables in numerical forest level optimization can have a great influence on the spatial distribution of fire resistance within the landscape. However, very different spatial structures may be equally good in terms of burned area. The burned area correlates closely with the mean fire resistance of stands, which is a non-spatial characteristic. However, the spatial distribution of fire resistance has a significant secondary effect; fragmentation of fire resistance decreases the total burned area if the mean resistance remains constant.

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