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Research article

A firebreak placement model for optimizing biodiversity protection at landscape scale

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ABSTRACT

A solution approach is proposed to optimize the selection of landscape cells for inclusion in firebreaks. It involves linking spatially explicit information on a landscape's ecological values, historical ignition patterns and fire spread behavior. A firebreak placement optimization model is formulated that captures the tradeoff between the direct loss of biodiversity due to the elimination of vegetation in areas designated for placement of firebreaks and the protection provided by the firebreaks from losses due to future forest fires. The optimal solution generated by the model reduced expected losses from wildfires on a biodiversity combined index due to wildfires by 30% relative to a landscape without any treatment. It also reduced expected losses by 16% compared to a randomly chosen solution. These results suggest that biodiversity loss resulting from the removal of vegetation in areas where firebreaks are placed can be offset by the reduction in biodiversity loss due to the firebreaks' protective function.

1. Introduction

Fire and living beings on our planet have molded each other in a relationship of harmonious co-dependence that for hundreds of millions of years was naturally controlled (McLauchlan et al., 2020). In recent times, however, this interaction has been thrown off balance by anthropogenic climate change and human activity itself (Kelly et al., 2020; Pausas and Keeley, 2021; Syphard et al., 2007). The available evidence suggests that the frequency and severity of large fires as well as fire-weather conditions are increasing as a result of human-induced warming (Jones et al., 2020; Westerling, 2016), which in turn has had a negative impact on both biodiversity (Keeley et al., 2019; Kelly et al., 2020) and human health through erosion, smoke release and greenhouse gas emissions, among other effects (Delfino et al., 2009; Dennekamp and Abramson, 2011; Johnston, 2009; Johnston et al., 2012). It is therefore essential that a better understanding of how to restore the positive co-existence of fires, biodiversity and human well-being be adopted as a global research priority.

Fire patterns can be modified through land cover arrangement and proper forest and vegetation management (Amiro et al., 2001; Cheney et al., 1993). Such activities, hereafter denoted fuel treatment, may include firebreak creation, prescribed burns, clearcutting and thinning, or some combination thereof North et al. (2015). Fuel treatment as part of fire management is a fire prevention method intended specifically to reduce a fire's rate of spread, intensity and flame length as well as curb crowning and spot fire development (Ager et al., 2010; Héon et al., 2014). Its effectiveness at landscape scale will depend on its ability to impede the progress of a fire (Aparício et al., 2022). Treatment measures may have negative impacts on biodiversity (Stevens et al., 2016), however, and should therefore be carried out only in areas that contribute little to it (see, e.g., Brown et al., 2009, Robinson et al., 2014). Unfortunately, these negative impacts and their future consequences remain poorly understood and difficult to quantify (Driscoll et al., 2010; Robinson et al., 2013). In the case of firebreaks, a fundamental question

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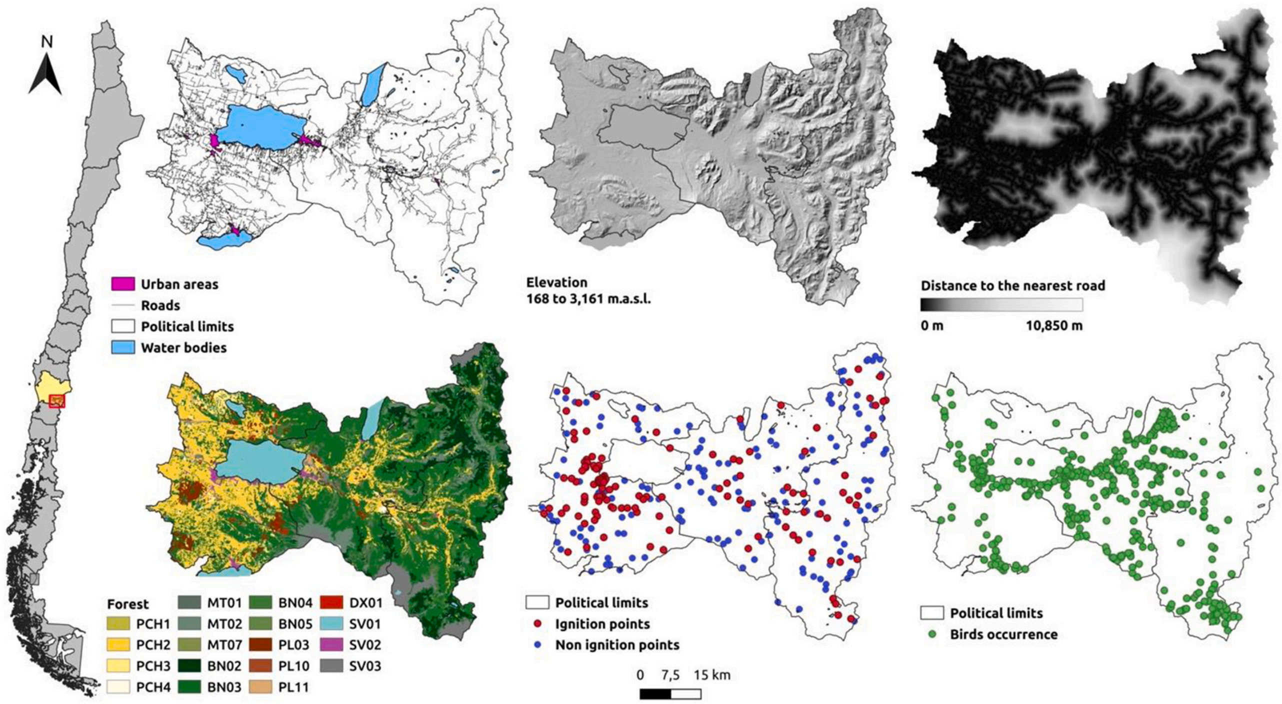

Fig. 1. Study area. At left is a map showing Chile's regional divisions, a local map highlighting urban zones and water bodies, and some explanatory variables (e.g., bird occurrence).

that thus arises is how to place them strategically across a landscape so that they (i) have a high probability of spatially overlapping with future wildfire events, thus increasing landscape fire-resistance; (ii) protect key biodiversity areas (e.g., wildlife habitat, endangered species sites); and (iii) do not excessively alter the habitat of the species in those areas, thus protecting their biodiversity.

Over the last three decades, several mathematical models and computational tools have been developed to tackle different aspects of fuel treatment, motivated primarily by the threat to human life and assets in fire-prone regions. These formulations have considered such factors as limited resources and budgets, the satisfaction of commercial demand for timber and environmental constraints (Ager, 2005; Chung, 2015; Pais et al., 2021a). The models proposed in the literature differ in their temporal and geographical scales, the latter varying from individual stands (local scale) to large landscapes containing many stands (landscape scale) or the area embracing a wildland-urban interface (Finney and Cohen, 2003). Some models take into account only current conditions (operational level; see Liu et al., 2013; Pais et al., 2021b,c) while others support planning for several decades (tactical or strategic level; see, e.g., Acuna et al., 2010; González-Olabarria and Pukkala, 2011; Gonzalez-Olabarria et al., 2023).

Current fire-management practices rarely include considerations of biodiversity (He et al., 2019; Chung, 2015; Regos et al., 2018). Moreover, there appear to be few studies that explicitly integrate biodiversity conservation objectives with fire preventive decisions. Rachmawati et al. (2018) propose a mixed integer programming (MIP) model that optimally schedules fuel treatments while simultaneously maintaining habitat availability. The authors address the issue of landscape fragmentation, which renders landscapes less fire-prone, and habitat connectivity, which indirectly favors biodiversity. But their model was tested using only a hypothetical random landscape comprising 100 grid cells with a single vegetation type, a single animal species and no spatially explicit simulator to model fire spread, making it difficult to evaluate the true effectiveness of the proposed solutions. The study does, however, constitute an important advance from a theoretical perspective, particularly in that it tackles conflicting objectives. León et al. (2019) contribute some improvements to the model, most notably the incorporation of neighbors in the direction of fire spread and better scalability for larger problems, but the demonstration of their approach is limited to a hypothetical landscape with no application of fire behavior systems to facilitate solution evaluation.

Thus, successfully balancing fuel treatment and biodiversity considerations remains a challenge facing managers in fire-prone ecosystems around the globe (Haslem et al., 2011; James and M'Closkey, 2003; Kennedy et al., 2008; Ucitel et al., 2003). In the present study, we hypothesize that the biodiversity loss resulting from the removal of vegetation in areas designated for firebreak placement can be offset by the reduction in biodiversity loss due to the firebreaks' protective action. Based on this tradeoff, we propose a method for identifying the optimal spatial distribution of firebreaks within a real and heterogeneous landscape that would reduce biodiversity losses due not only to the effects of fire but also to the negative impacts of firebreak construction. Our solution approach comprises an integrated wildfire spatial simulation and optimization framework including a prioritization metric that identifies crucial cells having a significant influence on the spread of fires across the landscape and their potential for ecological loss.

2. Materials and methods

2.1. Study area

The area chosen as the focus of our study is a real landscape located in the Araucanía Region of southern Chile (38°54′ S, 72°40′ W). It covers approximately 3,000 km^2 (see Fig. 1) and has a permanent human population of about 92,000 concentrated largely in the main urban zones (Villarrica, Pucón, and Curarrehue), although the number actually present is considerably higher in fire season (December to March) due to the influx of tourists drawn to the region by its natural attractions. Araucanía is one of the country's most fire-prone regions, registering the second highest number of hectares burned per fire between 2015 and 2020 (excluding 2017) according to the database maintained by the Chilean National Forest Corporation (CONAF). The local fire regime is associated mainly with human activity, characterized by the presence of roads and proximity to cities, with a high concentration of fire occurrence at the wildland-urban interface (Carrasco et al., 2021;

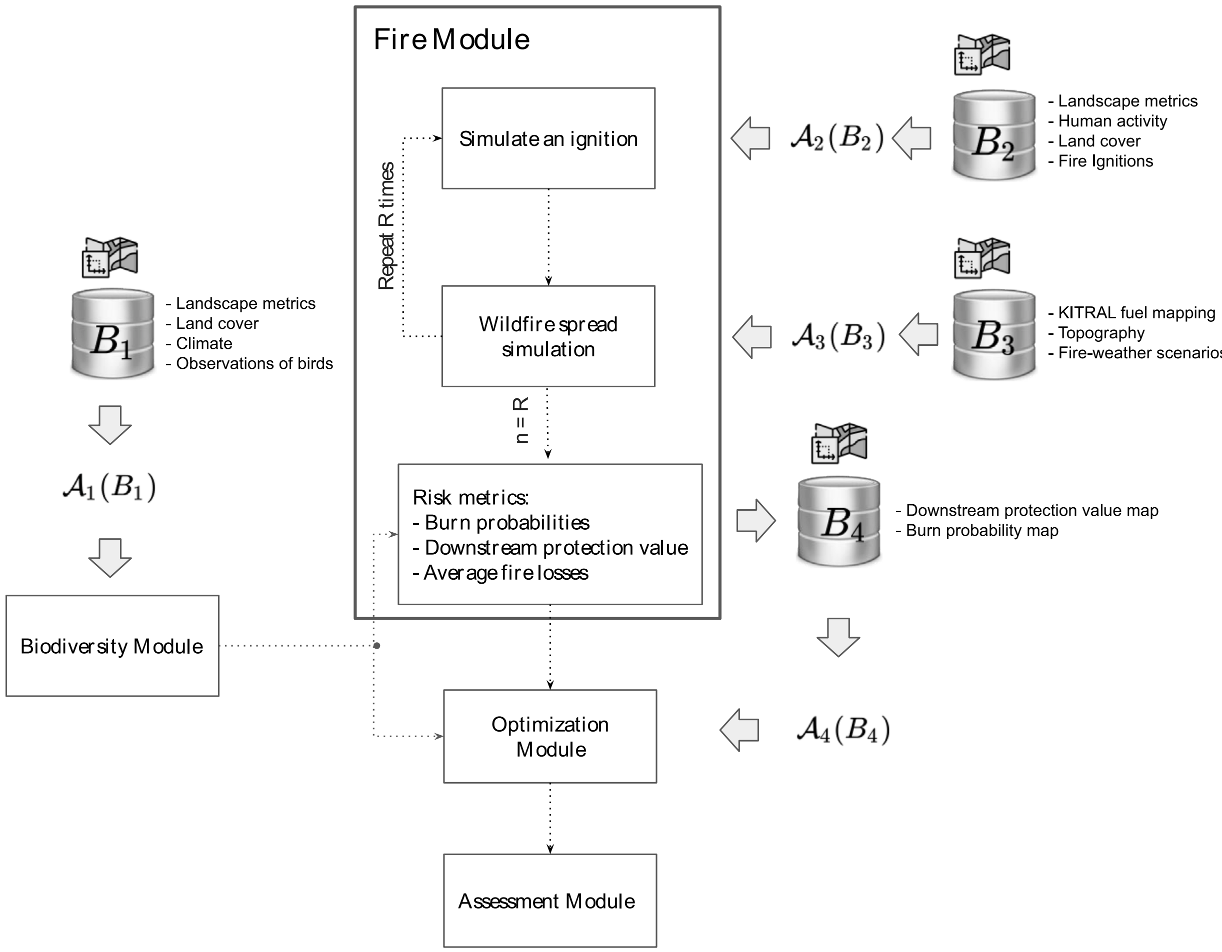

Fig. 2. Solution schematic.

Miranda et al., 2020). The area has a warm temperate climate with dry summers (Kottek et al., 2006) and a rugged topography, and is covered mainly by native forest (56.6%). It is also part of one of Chile's main biodiversity hotspots (Mittermeier et al., 2005).

2.2. Databases for modeling

A number of different algorithms and datasets were developed for use in the various steps of our methodology, as depicted in the solution schematic in Fig. 2. They are denoted B_1, B_2, B_3, B_4 and $\mathcal{A}_1$, $\mathcal{A}_2$, $\mathcal{A}_3$, $\mathcal{A}_4$, respectively. We write $\mathcal{A}(B)$ to denote the algorithm (or procedure) $\mathcal{A}$ that uses dataset B to generate its outputs.

Initially, we assigned a set of 71 variables to describe the landscape, model fire ignitions and species distributions and estimate biodiversity metrics, including variables for climatic, topographic, anthropogenic and land cover factors. We used a 100 m resolution land cover map from Zhao et al. (2016). This raster grid recognizes 10 land cover classes: croplands, native forest, forest plantation, grasslands, shrublands, wetlands, water bodies, impervious surfaces, barren land and snow/ice. The native forest class includes primary and secondary forest of Mediterranean and temperate forest types while the forest plantation class encompasses industrial tree plantations of exotic species of *Pinus* and *Eucalyptus genera*.

We also created a set of climate variables to represent data provided by ArClim (temperature, accumulated precipitation, evapotranspiration, and relative humidity), used a digital elevation model by Google Engine to obtain landscape elevation data, and calculated a number of the landscape metrics described in Hesselbarth et al. (2019) based on land covers types by Zhao et al. (2016). These metrics include patch cohesion index, mean Euclidean nearest-neighbor distance, largest patch index, land cover class composition percentage, total core area, mean patch area, patch density, and the Shannon and Simpson diversity indices.

Once this database was constructed, we selected the ten variables that best described the landscape on three different criteria: (i) variability, as indicated by the variation coefficient (Brown, 1998); (ii) number of unique values; and (iii) pairs of variables with a Pearson's correlation coefficient of less than 0.7 (see Table 1).

These variables were used to compute both the fire ignition probabilities and the biodiversity values (see Fig. 2). The former are based on fire and non-fire ignition points, both of which are geo-referenced in the study area (coded as 1 or 0, respectively) and linked to previously constructed variables. The ignition-point coordinates for each fire that occurred between January 2003 and December 2013 were obtained from a public fire occurrence database maintained by the (CONAF). The database contains 161 fire-starting points. To balance these data, 161 non-ignition points with a minimum distance to ignition points of 500 m were randomly chosen using the machine learning methodology described in Miranda et al. (2020). The resulting dataset is B_2 in our solution schematic (Fig. 2).

The B_1 dataset was constructed from only-presence observations of birds, retaining all species with at least 30 records. Only 55 bird species met this criterion, which was not the case for 109 other bird species (see Tab. S1) in the database of the Global Biodiversity Information Facility (GBIF) https://www.gbif.org/ for the Araucanía Region. Thus, we hereafter refer to the birds also as "fauna" and their biodiversity simply as "biodiversity".

To simulate multiple wildfires we needed a wildland fuel mapping and the fire-weather scenarios of the study area (Parisien et al., 2005; Pais et al., 2021a). For the first, we retrieved information from CONAF's 2014 Native Forest Cadaster, which uses the Chilean fire behavior system classification KITRAL (Pedernera and Julio, 1999), and digital elevation model (DEM) data on the landscape, both at 100 m resolution. For the second, we gathered random hourly meteorological data from the Pucón weather station (coordinates: 39°21′22″ S, 71°46′6″ W), chosen for its proximity to the study area. All the aforementioned variables constitute the B_3 dataset in our solution schematic (Fig. 2). The fire-weather scenarios were created using the following process: distributions of starting time and duration were extracted from the previous decade's wildfire records, prior to the publication of the CONAF Cadaster. Then, 100 weather scenarios were generated by randomly selecting a starting time and duration from the distributions, and extracting the corresponding continuous hourly records from the 2013 fire weather season (January to March). The weather scenarios include temperature, relative humidity, wind speed, and direction. To ensure the scenarios are representative of extreme conditions, only those scenarios that exceed the 95th percentile mean temperature were considered (see Fig. S1). Temperature and relative humidity were used to calculate the moisture content factor of dead and fine fuels while the wind speed and direction were used to calculate the *wind factor* in the fire rate of spread, as proposed in Julio et al. (1997).

Finally, the dynamic dataset B_4 was constructed from the ignition and fire spread iterative process generated in Module I (see Fig. 2). Two parameters were included in the dataset: burn probability (BP) and downstream protection value (DPV). These parameters are the inputs of our proposed optimization model for the spatial placement of firebreaks across the landscape, which is described below in Section 2.3. The module uses the fire ignition probabilities to choose an ignition location for each simulated wildfire. More specifically, to compute BP all simulated wildfires of a given iteration were recorded on a grid of the burned area, repeating the same process for each iteration. The outputs for all iterations were added to a cumulative grid. The BP for a given i cell (denoted $BP(i)$) was then computed as the ratio of the number of iterations that resulted in cell i being burned to the total number of iterations. The corresponding mapping of this metric is known as the Burn Probability Map (BPM) (Parisien et al., 2005).

To compute DPV, we first introduce the following notation. Let $\mathcal{F} = (\mathcal{N}, \mathcal{E})$ be the graphical representation of the landscape, $\mathcal{N}$ the set of cells (automatically fixed by the resolution of the data layers), and $\mathcal{E}$ the set of edges (each cell having 8 neighbors). Nodes can be associated with different attributes depending on the factor of interest such as fuel load, selling price per cubic meter, treatment costs per area, fuel type, biodiversity index and so forth. Similarly, edges can represent slope, distances between cell centers or transportation costs, among other possibilities (Pais et al., 2021a). When a fire occurs during a simulation, a messaging process is triggered between the nodes of $\mathcal{F}$ that generates a directed graph $\mathcal{F}_D = (\mathcal{N}_D, \mathcal{E}_D)$, where $\mathcal{N}_D \subseteq \mathcal{N}$ is the set containing all the cells burned during the replication. $\mathcal{E}_D$ is constructed from these signals to represent fire propagation between adjacent cells.

In specific terms, for all $j \in \mathcal{N}_D$ there is a directed subgraph $\mathcal{T}(j) = (\mathcal{N}(j), \mathcal{E}(j))$ of $\mathcal{F}_D$ such that $N(j) \subseteq \mathcal{N}_D$ and $\mathcal{E}(j) \subseteq \mathcal{E}_D$, so that the graph $\mathcal{T}(j)$ represents the shortest-path tree with root node j. For all $i \in \mathcal{N}$, $\mathcal{T}(i) = (\mathcal{N}(i), \mathcal{E}(i))$ is the shortest-path tree for which i is the root node. The downstream protection value $DPV(i)$ was defined in Pais et al. (2021b) as

$$DPV\,(i) = \sum_{j \in \mathcal{N}(i)} V_j \tag{1}$$

where V_j is an appropriate value at risk for the node/cell j. In our study, V_j will represent a biodiversity index that is assigned to each cell (see Fig. 2). Intuitively, DPV in a cell i represents the biodiversity values that are affected "downstream" from that cell i, given a simulated wildfire.

Table 1
Description of the 10 selected explanatory variables.

#	Variables
1	Distance (in meters) to the nearest city
2	Mean height (meters above sea level)
3	Natural forest patch cohesion
4	Distance (in meters) to the nearest road
5	Cumulated historic annual precipitation
6	Grassland patch cohesion
7	Mean slope
8	Total number of people by hectare
9	Shrubland patch cohesion
10	Simpsons Diversity Index

For multiple replicates/simulations (see Module I in Fig. 2), the DPV in a cell $i \in \mathcal{N}$ is estimated as the average of the DPVs calculated for each replicate. Note that a simulated fire r has a randomly selected weather (W_r) associated with it so $DPV(i)$ denotes the average of the downstream affected values dependent on the sampled fire-weather scenarios $\left(W_r\right)_{r=1:R}$ gathered in dataset B_3. For all of our experiments, we set $R = 1,000$.

2.3. Modeling approach

2.3.1. Modeling assumptions

The main assumptions underlying our solution approach may be summarized follows:

(i) Firebreaks are non-flammable. The application of firebreak treatment to a landscape cell implies the total removal of the vegetation fuel at that location.
(ii) All bird species that share the same habitat in a landscape site/cell are equally affected by fire.
(iii) All bird species that share the same habitat in a landscape location/cell are equally impacted by firebreaks.
(iv) If fire reaches a cell, the damage is total. Thus, 100% of its habitat is lost, affecting all species that inhabit the location with the same intensity. Post-fire effects are not considered.
(v) If a firebreak is sited in a cell, that cell is no longer suitable as a habitat for any species and all are equally affected. Post-treatment effects such as erosion or habitat fragmentation are not considered.
(vi) The firebreaks are implemented simultaneously across the landscape prior to the arrival of summer.

2.3.2. Models and methods

In this section we introduce the four $\mathcal{A}_x(B_x)$ modeling algorithms or procedures making up our solution methodology as set out schematically in Fig. 2. Brief descriptions of each of the four are presented below.

- $\mathcal{A}_1(B_1)$ denotes the series of steps in the procedure for generating the Combined Index Map (CIM) from dataset B_1. The first step was to construct a species distribution model for each bird species and then estimate the potential spatial distribution in each cell for which there was no record of presence. We used the CHE method (Carrasco et al., 2022), which was chosen mainly because it is less sensitive to outliers, preserves the interpretability of classical convex and elliptical envelope approaches, and adheres to the definition of Hutchinson's niche (Hutchinson, 1957).
  After applying the CHE approach to every species in B_1, we aggregated them at cell level using the Combined Index developed by Lisón and Sánchez-Fernández (2017) (hereafter, $Comb(j)$ denotes the combined index estimate for cell j). This aggregate metric combines the rarity and vulnerability of each species in a cell, as well as the richness of each cell. Richness is defined as the number of different species within a cell while rarity is the

inverse of the number of cells where it is present. Vulnerability was set following the International Union for Conservation of Nature categorization, using a descending integer scale from 5 to 1 where 5 is assigned to *critically endangered* species and 1 to those of *least concern* or not categorized. Between these extremes are 4 for *endangered* species, 3 for *vulnerable* species, and 2 for *near threatened* species.

- $\mathcal{A}_2(B_2)$ is the algorithm for generating a fire ignition probability map (IPM) from the B_2 dataset. This procedure follows the methodology proposed by Miranda et al. (2020), which consists in fitting a classification model (Bagged Decision Tree, BDT) to the "fire" and "non-fire" classes trained on B_2. The model's prediction performance is assessed using several statistical measures including *specificity*, *sensitivity*, overall *accuracy*, and the area under the curve (AUC). These measures are computed in the following manner:

$$\begin{aligned} specificity &= 100 \times \frac{TN}{FP+TN}, \\ sensitivity &= 100 \times \frac{TP}{TP+FN}, \\ accuracy &= 100 \times \frac{TN+TP}{FP+TN+TP+FN} \end{aligned} \tag{2}$$

where TP (true positive) and TN (true negative) are respectively the number of samples that are correctly classified as positive (presence class) and negative (absence class) observations in the cross-validation process. FP (false positive) and FN (false negative) are the corresponding numbers of samples that are misclassified. Therefore, *sensitivity* is the percentage of positive (presence class) observations that are correctly classified whereas *specificity* is the percentage of negative (absence class) observations that are correctly identified. The area under the receiver operating characteristic (ROC) curve (Breiman, 2001), denoted AUC, shows the true positive (TP) rate versus the false positive (FP) rate obtained by the model for different thresholds of the classifier output.

- $\mathcal{A}_3(B_3)$ is the algorithm for generating a spatially explicit wildfire simulation for each iteration in Module I. We developed this simulator, known as C2F+K (Carrasco et al., 2023), using as a basis the Cell2Fire simulator (Pais et al., 2021a) and the Chilean fire behavior system KITRAL (Julio et al., 1997; Pedernera and Julio, 1999).

  Although there are various fire simulation models used in different countries (e.g., Prometheus Tymstra et al., 2010, FARSITE Finney, 1998, FSPro Finney et al., 2011, FlamMap Finney, 2006, Cell2Fire Pais et al., 2021a, etc.), none of them incorporate KITRAL fuel models (or their equivalent) for simulating fires in Chile. An exception is the Wildfire Analyst System (Ramírez et al., 2011), which is a commercial software and thus not freely available to the scientific community.

- $\mathcal{A}_4(B_4)$ is the procedure for solving the mixed integer programming (MIP) model, which is used to locate the firebreaks. The model consists of a set of decision variables, an objective function and a set of constraints that limits the decisions' feasible solution space. Implementation and solution of the model was handled by the Pyomo optimization modeling package (Hart et al., 2017) and the GLPK Optimizer. The formulation of the model is detailed in the next subsection.

2.3.3. MIP for locating firebreaks

The formulation of the MIP model divides the landscape into a set of cells, each of which has an ecological value measured by a biodiversity index that will be totally lost if the cell is reached by a fire (see assumptions in Section 2.3.1). As already explained, the landscape is represented by graph $\mathcal{F} = (\mathcal{N}, \mathcal{E})$ that models its structure and connectivity.

The model's decision variables are denoted by the vector $x \in \{0,1\}^{|\mathcal{N}|}$, where $x_j := 1$ if cell j is selected to build a firebreak and 0 otherwise. As well as a technique for impeding or stopping a fire's progress, firebreaks can be used as an area to facilitate fire suppression work (Ascoli et al., 2018), but this possibility is not considered here.

The objective function is constructed so that the selection of cells prioritizes those that (i) have the greatest potential for wildlife habitat damage due to fire (weighted by the Combined Index), and (ii) have a low ecological value (as a sink). Note as regards the latter point that since we assume the ecological value of a cell is lost when its vegetation is removed and replaced by a firebreak, the cells selected for treatment should be those that result in as low a loss as possible while protecting the landscape from dangerous wildfires.

In formal terms, point (i) above can be expressed as $\sum_{j\in\mathcal{N}} DPV(j) \cdot x_j$ and point (ii) as $\sum_{j\in\mathcal{N}} Comb(j) \cdot x_j$, which combine to make up the objective function as follows:

$$z = \sum_{j\in\mathcal{N}} DPV(j) \cdot x_j - \sum_{j\in\mathcal{N}} Comb(j) \cdot x_j. \tag{3}$$

This in turn is rewritten as $z = \sum_{j\in\mathcal{N}} [DPV(j) - Comb(j)] \cdot x_j$, where $DPV(j) - Comb(j)$ can be interpreted as the *effective marginal protection contribution (EMPC)* due to the construction of a firebreak in cell j.

In practice, due to the high cost of constructing firebreaks and the ecological damage they may do to the ecosystem (runoff and erosion increase, reduction of soil infiltration rates, etc.), they can be applied only to a small percentage of the landscape (Oliveira et al., 2016; Jingan et al., 2005). In our case, we used a range of percentages not exceeding 1% of the total flammable cells in the study area. We model this constraint by introducing a parameter α with values between zero and one. This constraint is expressed formally as

$$\sum_{j\in\mathcal{N}} x_j \le \alpha \cdot |\mathcal{N}|. \tag{4}$$

The expected loss (EL) is defined in terms of the burn probabilities (BP) computed in Module I as follows:

$$EL_V(\mathcal{F}) = \sum_{j\in\mathcal{N}} BP(j|\mathcal{F}) \cdot V_j \tag{5}$$

where V_j is a generic notation for the landscape values at risk. We then impose that any feasible solution x must ensure the treatment-related losses (TRL) do not exceed a certain fraction $\beta \in [0,1]$ of the expected loss before the treatment. Thus, β is the tolerance to treatment-related losses (TTRL). This constraint can then be written as

$$\sum_{j\in\mathcal{N}} Comb(j) \cdot x_j \le \beta \cdot EL_{Comb}(\mathcal{F}). \tag{6}$$

The complete MIP model can now be formulated as follows:

$$\begin{aligned} max \quad & z_\alpha = \textstyle\sum_{j\in\mathcal{N}} EMPC(j) \cdot x_j \\ s.t. \quad & \\ & \textstyle\sum_{j\in\mathcal{N}} x_j \le \alpha \cdot |\mathcal{N}|, \\ & \textstyle\sum_{j\in\mathcal{N}} Comb(j) \cdot x_j \le \beta \cdot EL_{Comb}(\mathcal{F}), \\ & x_j \in \{0,1\}, \quad j \in \mathcal{N} \end{aligned} \tag{7}$$

A solution of the MIP model (7) will henceforth be referred to as an *optimal firebreak plan* or simply as an *optimal plan*.

Finally, to assess the solutions given by our optimization approach, we compared the Net Protective Effect (NPE) of the various firebreak plans. NPE was defined as follows. Let $\mathcal{F}$ be the landscape before treatment and $\mathcal{F}_\tau = (\mathcal{N}_\tau, \mathcal{E}_\tau)$ the graph that represents the landscape after an optimal plan is applied. Also let $X^\tau = (x_j^\tau)_{j\in\mathcal{N}}$ be the binary vector representation of the firebreaks assigned by plan τ. Then the NPE of τ is given by

$$NPE(\mathcal{F}, \tau, \vec{V}) = EL_V(\mathcal{F}) - (EL_V(\mathcal{F}_\tau) + \sum_{j\in\mathcal{N}} v_j x_j^\tau) \tag{8}$$

where $\sum_{j\in\mathcal{F}} v_j x_j^\tau$ is the treatment-related losses. Intuitively, we calculated the NPE as the difference between the Expected Losses Before

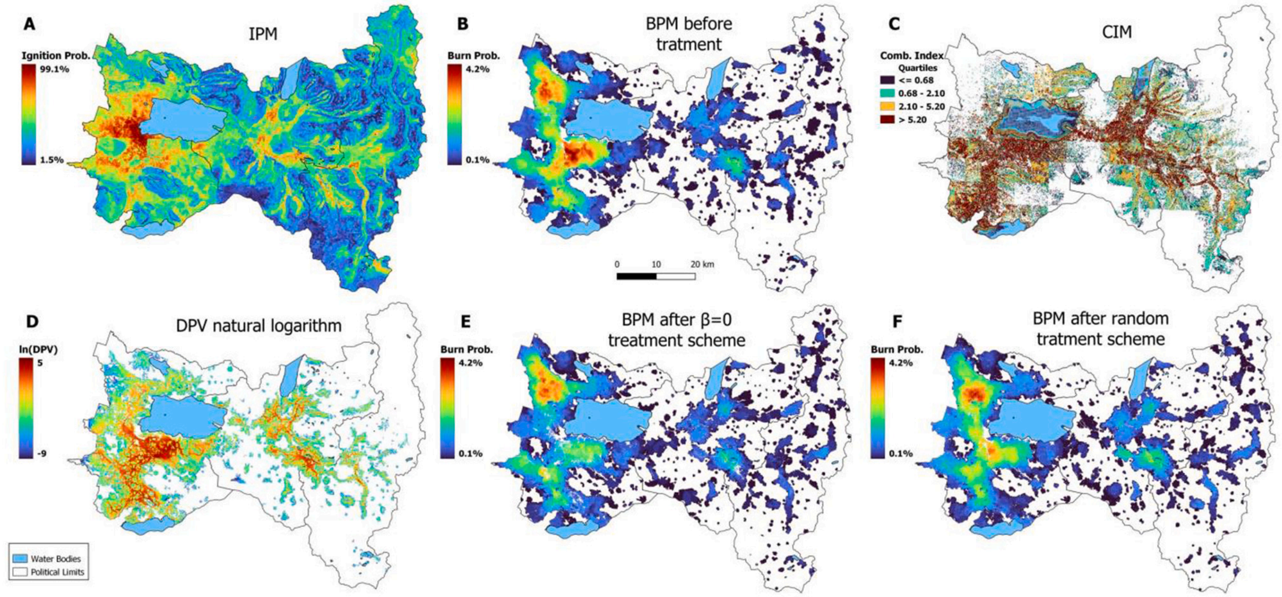

Fig. 3. Maps showing the results for each metric: A: Fire Ignition Probability Map; B: Burn Probability Map before any treatment; C: The Combined Index Map; D: The DPV natural logarithm map; E: BPM after the optimum treatment plan; and F: BPM after the random plan.

Treatment (ELBT, which is $EL_{Comb}(\mathcal{F})$) and the sum of the TRL and the Expected Losses After Treatment (ELAT), that is, $EL_{Comb}(\mathcal{F}_\tau) + \sum_{j\in\mathcal{F}} \upsilon_j x_j^\tau$.

To succinctly summarize, our methodology involves the following procedures: Initially, BP and DPV metrics are calculated through the utilization of simulated fires on the untreated terrain. Subsequently, these calculated metrics are incorporated as parameters in the optimization problem that we have formulated, which is then solved to determine the optimal location of firebreaks on the landscape. Finally, after the modification of the landscape, we repeat the process of conducting fire simulations, but this time, only on the treated terrain. This approach allows for a more accurate evaluation of the effectiveness of the proposed solution.

3. Results and discussion

This section sets out and discusses the results of our study, presenting first an accuracy assessment of the prediction models in the solution schematic and then an analysis of the optimal firebreak plan obtained for our study area.

3.1. Accuracy assessment of the prediction models

3.1.1. Species distribution models and CIM

For each of the 55 bird species, we built a CHE model and used it to predict presences or absences in cells for which there were no records. To evaluate the accuracy of the CHE bird species models, we compared their results with a random prediction model as follows. First, for each species we generated as many random predictions as did the CHE model. For example, if the CHE approach generated 150 predictions for species i, we generated 150 random predictions for that same species. We then made two calculations: (1) the ratio of true positives to the total number of predictions, and (2) the difference between the random predictions and those predicted by CHE, which consisted simply in deducting the number of predictions on which the two models coincided from the total number (150 in the above example) and dividing the result by that same total. Therefore, as was expected given the CHE model's construction, when all of the data were used to construct the model, the ratio of true positives produced by CHE varied between 75.6% and 95.8%, with an average of 85.2%, whereas the ratio for the random assignment varied between 0.0% and 32.0%, with an average of 12.9%. The average difference between the two approaches across all bird species was 86.4%, ranging from a minimum of 68.5% to a maximum of 97.7%.

The species distribution model was then used to increment the number of presences. The original number of records was 5,286 spread across just 725 different cells, but after applying the CHE approach, the total number of predicted occurrences increased to 2,774,961 spread across 56,332 cells, the equivalent of 42% of the landscape cells having at least one predicted presence. Hence, the number of presences was increased 525 times and the area of the landscape with at least one observation 216 times.

After generating the potential distribution map of each species, we aggregated them at cell level using the Combined Index. The CIM is depicted in Fig. 3-**C**.

3.1.2. Fire-Ignition probability map

Our results show that the BDT model effectively and accurately predicted the fire- and non-fire ignition points, with a *sensitivity* of 65.0%, a *specificity* of 76.7%, an overall *accuracy* of 70.9%, and an AUC of 0.76, all averages after cross-validation. These results are comparable with those reported by similar studies (see, e.g., Carrasco et al., 2021; Moayedi et al., 2020; Gholamnia et al., 2020; McWethy et al., 2018).

Note that BDT is an ensemble method, meaning that different classification models (called "weak learners") are combined to obtain a "master classifier" that generates a more robust prediction through a voting process producing values between 0 and 1. Here, higher values favor class "1" (fire) while lower values favor class "0" (non-fire). (For more details, see Miranda et al., 2020.) We denote these continuous values "fire-ignition probabilities", which are obtained by applying the BDT model to each landscape cell and then using them to build the Ignition Probability Map shown in Fig. 3-**A** (for a larger image, see Fig. S3).

3.2. Firebreak placement solution

The spatial overlap between wildfires and the combined index map was evaluated using stochastic fire simulations based on the IPM, as is shown in Fig. 3. This overlap is illustrated by the DPV map (Fig. 3-**C** and Fig. S4). The results allowed us to assess the solutions generated by

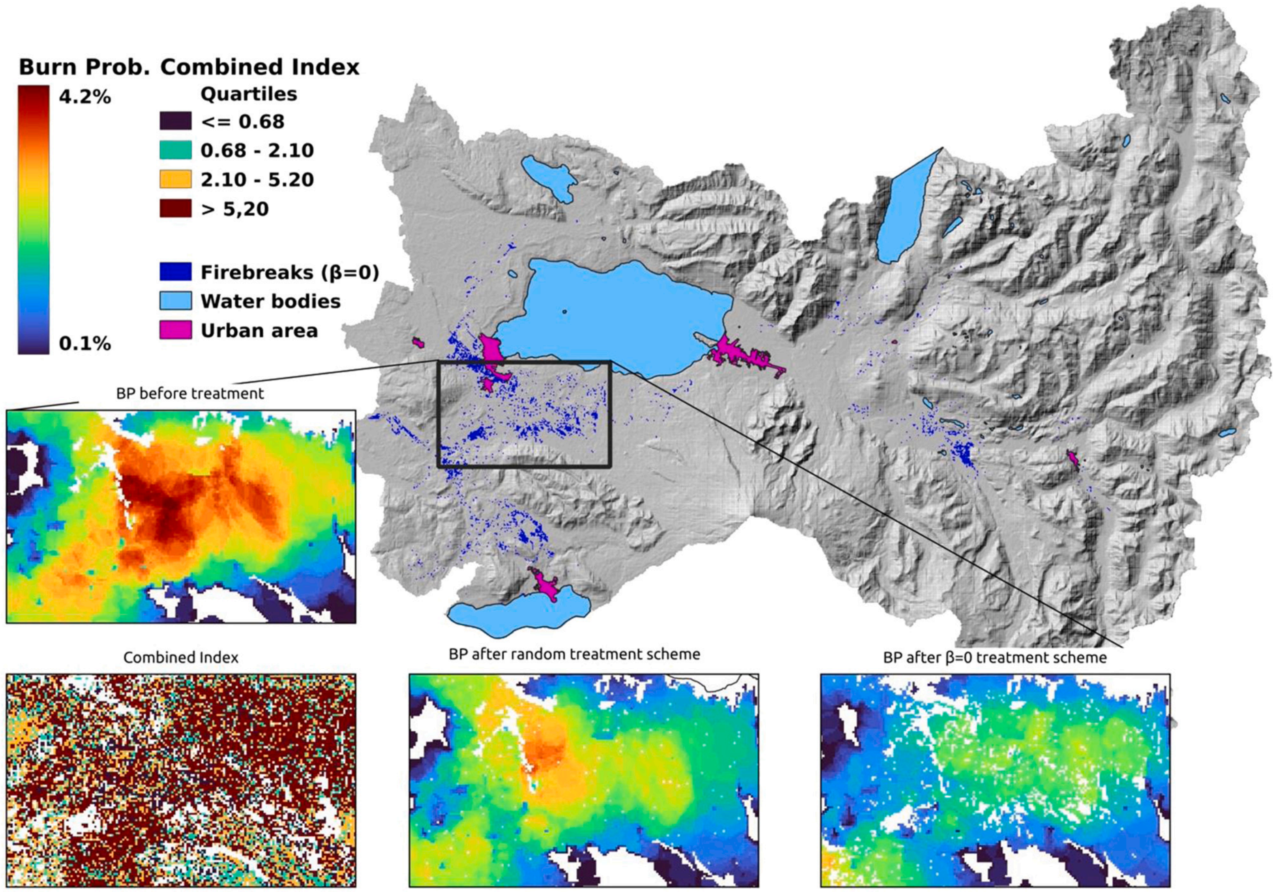

Fig. 4. Results Highlights.

our optimization model. We compared them with a random firebreak placement and an untreated landscape to determine the impact of the optimal plan generated by the MIP model (see Fig. 3-**E**, **F** and **B**, respectively).

The foregoing is clearly illustrated in the area located on the lower left-hand side of the large lake as highlighted in Fig. 4. Both the burn probability and the combined index were high before any optimal plan was applied. The DPV values in that area were also high, as can be seen in Fig. 3-**D**, meaning that for $\beta = 0$ there were a large number of firebreaks (Fig. 4). Thus, we observed a great decrease in BP as a result of applying the optimal plan. By contrast, a smaller reduction was obtained with a random plan, as shown in Fig. 3-**F**.

We tested twelve different plans, in all cases assuming that due to a capacity constraint, only 1% of the flammable cells could be treated ($\alpha = 0.01$). The twelve included a random firebreak placement plan and 11 solutions generated by our decision-making approach obtained by varying which $\beta \in \{0, 0.1, \ldots, 0.9, 1\}$. The solutions were then compared with the baseline untreated landscape.

Note that other studies have considered $\alpha > 0.01$ (e.g. Oliveira et al., 2016). In the present case, however, treating more than 1% would be impractical due to the high biodiversity levels and large numbers of protected areas and natural parks in the region under study.

As expected, the worst case was the random firebreak placement (see Fig. 3-**F**), which registered an NPE of −4,776 (in terms of the combined index). This is the equivalent of 130% of ELBT, meaning that the random plan increased losses to 30% above that level. The result is due mainly to the TRL, since even though the plan was able to reduce the landscape's BP (from 4.2% maximum to 3.4% maximum) and thus also reduce ELAT (17% less than ELBT), the destructive impact of its implementation brought about relatively greater losses (47% more than ELBT).

The respective relationships of NPE (Eq. (8)) and the objective function value (Eq. (3)) to β are graphed in Fig. 5. As can be seen, in the NPE case the relationship was an inverse one. For $\beta \leq 0.45$ approximately, NPE was positive, indicating that the protective effect of the firebreak plan offset its negative impacts. On the other hand, for $\beta \geq 0.45$ the opposite was true; the destructive effects of the treatment scheme exceeded its protective benefits. There is thus a threshold beyond which the benefits of strategically sited firebreaks are outweighed by their negative impacts on the habitat.

By contrast with NPE, the relationship of the OF value to β was direct. In both cases, the behavior highlights the fact that even though DPV very effectively captures fire behavior within the landscape and its potential effect on the values to be protected, it overestimated the protective effects of the firebreak network. This was so mainly because DPV considers the effect of each firebreak on the untreated landscape separately and thus does not take into account the effects of a previously assigned firebreak when placement the next one. Finally, the best results were achieved when $\beta = 0.0$. With that optimal plan the NPE rose to 1,113 (in terms of combined index), meaning that the policy saved 30% of the landscape value compared to ELBT. The superior performance of this solution was due to the fact that it does not incur in any treatment-related losses thanks to the effect of the TTRL constraint (Eq. (6)), even though ELAT in this case was the highest for any β value and second only to that for the random plan where ELAT/ELBT = 0.83.

3.3. Implications and limitations

The assumptions underlying our solution approach to fire management and conservation efforts have important implications and limitations that must be considered. Studies have shown that the total

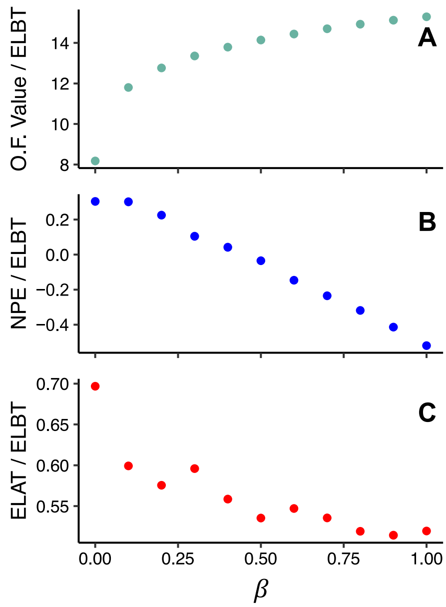

Fig. 5. Objective function value, Net Protection Effect (NPE) and ELAT (Expected Loss After Treatment) as a fraction of the Expected Loss Before Treatment (ELBT) for values of β, with $\alpha = 1\%$.

removal of vegetation fuels from an area, as implied by fire treatments, may not always be effective in preventing fires or reducing fire damage because fire behavior and weather conditions can vary widely across landscapes (McKinney et al., 2022). In addition, the assumption that all bird species in a habitat are equally affected by fire and firebreaks may not reflect the unique ecological and behavioral characteristics of each species, which may respond differently to fire disturbance (Lehmkuhl et al., 2007). Similarly, the assumption that all post-treatment effects, such as erosion or habitat fragmentation, are negligible is not always accurate, as these effects can significantly affect the long-term health of ecosystems (Mullu, 2016), and even seemingly innocuous practices could have adverse effects on species such as amphibians (Pilliod et al., 2003). Finally, the assumption that firebreaks can be implemented anywhere on the landscape may not be feasible, as site-specific factors such as topography, vegetation type, and proximity to human infrastructure may require a more flexible and adaptive approach (Agee et al., 2000). Therefore, it is critical to consider the limitations of these assumptions and incorporate a more holistic and adaptive approach that balances conservation objectives with the practical realities of fire management, as supported by previous research in the field of fire ecology.

In Chile, firebreaks are typically created through a collaborative effort between government agencies and private landowners. As mentioned above, the primary agency responsible for managing and coordinating fire prevention and control efforts, including the creation of firebreaks, is CONAF. Despite these efforts, there is currently no system in place for generating fire-resistant and/or resilient landscapes, with focus instead having been placed for decades on a reactive approach through firefighting. This study has emerged from the necessity to address this issue and has been developed in collaboration with CONAF through a FONDEF project (which is acknowledged). Although it remains a proof of concept, and further considerations are required prior to its implementation, we are confident that with the relevant information, we can identify realistic solutions to address the context of the national territory.

4. Conclusions

This study proposed an approach to optimizing the selection of landscape cells for potential replacement by firebreaks that would reduce the expected loss of habitat from wildfires. The methodology involved linking spatially explicit information on a landscape's ecological values, historical ignition patterns and fire spread behavior. Our approach aims to provide a solution to the question of how best to prepare a landscape for the summer season, when the risk of fire is high. The proposed approach involves the construction of firebreaks in the fall and spring seasons, followed by regular maintenance. In the event that firebreaks fail due to inadequate maintenance, our methodology provides the ability to evaluate their revised effectiveness through repeated simulations and/or modification of the optimization model to include the functioning portion of the firebreak. It should be noted, however, that this approach has certain limitations that may affect its effectiveness in real-world scenarios.

The firebreak placement problem was formulated as an MIP model containing (i) a set of binary variables for each cell representing the decision whether or not to include it in a firebreak (ii) a set of constraints limiting the decisions' feasible solution space, and (iii) an objective function that captures the tradeoff between the direct loss of biodiversity due to the elimination of vegetation in areas designated for firebreak placement and the protection provided by the firebreaks from losses due to future wildfires. The main parameters of the MIP model were determined through a combined process of computing stochastic ignition probabilities (obtained from a machine learning model), spatially explicit simulation of fire propagation (using a simulator developed for the job called C2F+K, available in a GitHub repository), and estimation of bird biodiversity indices (using a species distribution model embodying the CHE approach applied to each species).

Our study has produced several solutions based on the beta parameter. For beta values between 0 and 0.45, we have obtained positive trade-off values that balance the loss of biodiversity due to the placement of firebreaks with the firebreaks' protective value, providing evidence in favor of our hypothesis. Our optimization model, when applied to $\beta = 0$, demonstrated a significant reduction in the expected losses due to wildfires on a Combined Index by 30% compared to a landscape without any treatment. Additionally, the optimal solution reduced expected losses by 16% relative to a randomly chosen solution, without incurring habitat loss due to the placement of firebreaks in low combined-index locations. As a result, total losses were reduced by 70%.

It is noteworthy to emphasize that the scope of this study is limited to a particular case study, and therefore, the applicability of our model and the associated solution is contingent upon the specific characteristics and values at risk of the landscape in question. Nonetheless, we have applied our methodology to other landscapes with identical values at risk ($V_j = 1$, for all j), with the objective of finding a firebreak plan that minimizes the extent of the burnt area, regardless of the specific elements that are burnt. Through of this study, we have demonstrated the significance of cell selection criteria to firebreak, and have evaluated and compared various criteria such as Burn Probability, Betweenness Centrality, Fire Protection Value, and ultimately concluded that the Downstream Protection Value (DPV) criterion is superior to the others (for more details, see Pais et al., 2021b). DPV's superiority over other metrics lies in its ability to capture the potential damage that would occur if fire reached a given cell, while taking into account less local aspects of the cell. Therefore, our research thus far suggests that our methodology is capable of being applied to a variety of landscapes and distributions of values at risk, however, it is acknowledged that further research is necessary to fully validate its generalizability.

Finally, we note that firebreaks were the only fuel management measure considered in this study. Future research could extend the approach proposed here to embrace other fuel treatment techniques that may have a smaller impact on species habitat and landscape biodiversity. It would also be advisable to take into account the constraints imposed by environmental, budgetary, and legal regulations, as this could result in solutions that are less limited to local areas and have a wider geographical distribution than those obtained in this preliminary study.

CRediT authorship contribution statement

Jaime Carrasco: Conceptualization, Investigation, Methodology, Visualization, Writing – original draft. **Rodrigo Mahaluf:** Visualization, Data curation, Methodology, Writing. **Fulgencio Lisón:** Data curation, Writing; Review. **Cristobal Pais:** Methodology, Editing. **Alejandro Miranda:** Data curation; Review. **Felipe de la Barra:** Data curation, Review. **David Palacios:** Data curation, Review. **Andrés Weintraub:** Supervision, Review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.118087.

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