Journal of Environmental Management 360 (2024) 121001

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Discussion

Improving the evaluation of spatial optimization models for prioritizing landscape restoration and wildfire risk reduction investments

Alan Ager *

USDA Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory, 5775 US Highway 10W, Missoula, MT, 59808, USA

1. Introduction

Prioritizing investments in restoration, risk reduction, and conservation programs is an important part of the planning process to develop strategies for a wide range of resource management issues in the US and elsewhere (Ball et al., 2009; Noss et al., 2009; Kukkala and Moilanen, 2013; Chazdon and Guariguata, 2018; Pohjanmies et al., 2019; Strassburg et al., 2020; Duchardt et al., 2021). Prioritization systems have been developed for application at a range of scales, and typically involve multiple objectives and various schemes for optimization and tradeoff analyses (Noss et al., 2009). Spatial considerations play an increasingly important role in most if not all of these planning systems to meet various landscape adjacency and connectivity constraints over space and time. (De Pellegrin Llorente et al., 2017; Cao et al., 2020). Rigorous prioritization is warranted given that resources are generally limited and wide spatial variation in management targets and outcomes exists in many ecosystems of concern. Incorrect or non-optimal prioritization can contribute to failed objectives and wasted resources (Brudvig, 2017; Iftekhar et al., 2017). Integrating priorities into planning can help communicate restoration investment needs and outcomes to stakeholders in collaborative planning efforts (Eaton et al., 2019; Riddell et al., 2019).

In the western US where expansive tracts of public lands are increasingly impacted by ecologically and socio-economically destructive wildfire, prioritization is a key component of implementing federal risk reduction and restoration programs to address a large backlog of treatment needs under significant budget and capacity constraints (Ager et al., 2021). A number of prioritization systems have been developed over the past two decades (e.g., Reynolds, 2001; Hessburg et al., 2006; Ager et al., 2011) but few have incorporated the optimization technologies increasingly used in systematic conservation planning (Strassburg et al., 2020; Zhang and Li, 2022). This gap led to the development of the ForSys planning system as a tool for mainstreaming spatial optimization to support federal planning at a range of scales (Day et al., 2023, ForSys Research Consortium, 2024). ForSys was designed to bridge forest landscape planning, spatial optimization, and the science and literature on scenario analyses that emphasize the importance of examining large arrays of management scenarios and considering uncertain future disturbance (Peterson et al., 2003; Polasky et al., 2011). The program uses a relatively simple greedy heuristic to optimize the selection of treatment units into optimized project areas while considering constraints and treatment thresholds. Numerous case studies have shown the model can build and prioritize project areas that are generally consistent with expectations of field managers and resource specialists in terms of location, stands to treat, and economic outcomes across large tracts of land (e.g., 10^6 ha, Day et al., 2023). Most recently the model was used to identify priority landscapes for the USFS Wildfire Crisis Strategy (USDA Forest Service, 2022). In this work the model was used to identify and prioritize 250,000 ha “firesheds” that were prioritized based on the likelihood of wildfire transmission from National Forests to the adjacent developed areas. (Ager et al., 2021). The analysis included a spatially explicit 10-year treatment schedule by national forest and planning area (25,000 ha) within each fireshed. The USFS broadly adopted the analysis to guide forest and fuel management investments as part of implementing the Wildfire Crisis Strategy.

The expanding application of ForSys motivated a group of academic researchers independent of the original developers to scrutinize the greedy heuristic and its performance compared to exact mixed integer linear programming (henceforth MILP) (Murray et al., 2022; Murray and Church, 2023; Pludow et al., 2023). Parallel investigations of heuristics versus mixed MILP have also appeared in assessments of the Marxan platform widely used in systematic conservation (Beyer et al., 2016; Schuster et al., 2020). The articles that examined ForSys reported sub-optimal solutions (up to 6.9% less optimal) by the greedy heuristic compared to a new MILP algorithm created to replicate ForSys functionality for a study area in the Sierra Nevada in California. More significant differences between ForSys and the MILP solutions were reported for a bi-objective solution. This independent assessment of the ForSys model naturally sparked interest by the ForSys developers since ForSys is an institutional product of the USDA Forest Service (henceforth

* Corresponding author.
E-mail address: alan.ager@oregonstate.edu.

https://doi.org/10.1016/j.jenvman.2024.121001
Received 5 February 2024; Received in revised form 17 April 2024; Accepted 21 April 2024
Available online 21 May 2024
0301-4797/

USFS), Research and Development and an accurate critique of the model and context for its application is warranted. Moreover, one of the ForSys optimization heuristics has been incorporated into both commercial (Land Tender, Vibrant Planet, 2023) and public domain (Planscape, Planscape, 2024) planning platforms under collaborative agreements with the Forest Service. The latter systems are cloud hosted and use geospatial interfaces to create a convenient platform for environmental analyses as part of risk reduction and restoration. Of the three comparison articles, the most recent and critical of the ForSys optimization heuristic was published in this Journal (Pludow et al., 2023) and was of particular concern to the ForSys research team (ForSys Research Consortium, 2024) since the article included a comprehensive list of studies using ForSys, lending the appearance of an in-depth and authoritative review of the model and its application.

In this paper, I first review the technical description of ForSys presented in Pludow et al. (2023), Murray et al. (2022), and Murray and Church (2023) (henceforth "comparison articles") noting significant issues and concerns, and then re-examine their findings regarding the performance of the alternative MILP optimization approach. Particular attention is given to the description of the ForSys optimization heuristic, and the problem formulation used for the comparison. I then discuss parallel literature from the biodiversity conservation field concerning the relative merits of heuristics versus MILP based approaches. Several conclusions are presented including recommendations that a broader set of criteria are used for evaluating spatial optimization models beyond finding exact optima for real world natural resource planning problems related to restoration, wildfire risk reduction, and biodiversity conservation.

2. Methods

The description of the ForSys model in the comparison articles and the MILP formulation created to replicate it was studied to ensure that the latter was replicating the functionality of the former. The articles were further examined for any ForSys input parameters, especially those that control the search behavior of the heuristics used to generate the reported solutions. The formulation of the example spatial planning problem used in the comparison was also examined especially in relation to published ForSys case studies. Of particular interest was whether the Murray et al. (2022) algorithm as applied in Pludow et al. (2023) replicated the functionality of ForSys as demonstrated in case studies. The data were then acquired for the 48,000 ha SERAL project on the Stanislaus National Forest used in the comparison articles and attempts were made to replicate the results using a wide range of parameters and the same data set. This analysis focused on geographic subarea 214 with 1343 polygons, and the two metrics used in Pludow et al. (2023): (1) expected net value change which measures loss and benefits from wildfire, and (2) a measure of departure from resilient conditions in the stand (USDA Forest Service 2021).

The scope of the paper was then expanded to discuss the relative merits of MILP versus heuristic approaches for solving conservation planning problems (Ball and Possingham, 2000). This discussion included recent literature reporting several newer planning platforms that use spatial optimization to identify efficient solutions to a range of conservation problems.

3. Results and discussion

3.1. Comparison of the ForSys heuristic with MILP

A detailed review of the comparison articles found multiple discrepancies regarding the description of the ForSys optimization heuristic. The comparison case study on the SERAL project was a substantially different problem formulation than the 24 published case studies tabulated in Pludow et al. (2023). Starting with the Introduction of the most recent paper, Pludow et al. (2023) states that the ForSys heuristic has been integrated into the commercial Land Tender planning platform (Vibrant Planet, 2023) but did not note that Land Tender uses an entirely different heuristic (Patchmax, Evers et al., 2023a) developed specifically for the R version of ForSys (ForSysR, Evers et al., 2023b) also not mentioned, versus the C++ version (ForSysX) used for the comparisons. Patchmax uses a network search approach based on Dijkstra's algorithm (Dijkstra, 1959; Evers et al., 2023a), not the algorithm in ForSysX. Thus, none of the results or discussion in the comparison articles are relevant to the Land Tender platform, nor to the two studies that used ForSysR (Belavenutti et al. 2022, 2023) tabulated in Table 1 within Pludow et al. (2023). Note that the newer Planscape planning platform (Planscape, 2024) being developed by the Spatial Informatics Group also integrates Patchmax as the optimization algorithm.

The Introduction sections in all three comparative assessments also state that the mathematical definition of the ForSys greedy heuristic is inadequately defined, especially the adjacency constraint (Pludow et al., 2023), and to some extent I agree that the algorithm could have been better described in prior publications (Supplement Fig. S1). However, the need to mathematically define adjacency is only required with mathematical programming models, whereas the ForSys algorithm simply enforces it when polygons are added to projects (Ager et al., 2016). The users are required to build an adjacency matrix within ForSys prior to executing a scenario, and hence it should be apparent that the matrix is used to aggregate polygons into projects (Supplement Fig. S1). Note also that the Patchmax algorithm used in ForSysR, Land Tender and Planscape operate on a connectivity network of polygons based on either adjacency or proximity, allowing the algorithm to skip over adjacent polygons to optimize the objective function. Aggregation is controlled by a priority-based distance penalty applied to a shortest-path network search algorithm (Evers et al. 2023a, 2023b). Note also that the formulae offered in the comparative assessment articles (Murray et al., 2022, Eq 5) specify that the constraint is based on project area, whereas ForSys can use any sort of activity constraint variable as demonstrated in case studies (Ager et al., 2021; Day et al., 2023).

A more significant issue is that MILP equations (e.g. Murray equation 2) specify that adjacency requirements apply specifically to treated stands which contradicts the application of ForSys in all of the published case studies tabulated by Pludow et al. (2023), and also contradicts operational practices for designing landscape forest and fuel management projects. ForSysX enforces adjacency among all polygons in a project area, with treatments allocated based on user-input treatment thresholds. Pludow et al. (2023) stated that enforcing adjacency among treated stands was an option in ForSys, but in reality this spatial property can only be achieved in a solution by treating every stand, which is not a realistic scenario on a typical prioritization problem. In summary, the significant re-casting of the core ForSys optimization problem in the comparison articles undermines their findings.

The comparison articles used data from the SERAL restoration project on the Stanislaus National Forest in the Sierra Nevada (USDA Forest Service 2024). The study area was divided into six smaller geographics units (303 ha–19,555 ha (Pludow et al., 2023) and analyzed individually for reasons not specified although it can be speculated that it was due to computational constraints. The optimization process to compare the MILP formulation with the ForSys heuristic was to identify 100-acre aggregates of adjacent stands that maximized two different objectives, assuming that every stand in the 100-acre (40.5 ha) patch required treatment, (Murray et al., 2022, Figs.4–8, Murray and Church, 2023, Figs.3–5, Pludow et al., 2023, Figs.2–4). In one scenario, multiple treatment patches were optimized in each sub area until 25% of the study area was included in a patch although the results focus on the optimality of a single patch. This problem formulation is a significant departure from the intended ForSys application where the model is used to partition landscapes on the order of 10^6 ha (Day et al., 2021) into contiguous project areas (not a few very small contiguous treatment patches) that are optimized based on the objective contribution from stands that are treated. In ForSys, when the optimization option is invoked, adjacency is enforced among stands in the project area, not among treated stands, in order to build planning areas that can subsequently be prioritized for implementation as part of outyear planning (Day et al., 2021) and used to analyze tradeoffs in the case of multiple objectives. Extensive testing and field application has shown that the ForSys heuristic generates projects that resemble those in the real world in terms of size, shape, treatment density, and priority for management (Ager et al., 2016). By contrast, the application in the comparison articles used predefined project boundaries ("geographic units" in Pludow et al. (2023)) and identified contiguous treatment patches by aggregating a small number of stands (<20) to build a 100 acre patch, rather than optimize project areas (e.g. 20,000–50,000 ha) based on the objective contribution of hundreds to thousands of polygons. The relatively large stand size relative to the 100-acre patch significantly constrained the solution space of the problem (i.e. some stands exceeded the patch size) (Supplement Fig. S2).

Despite the atypical optimization problem presented to ForSys in the Murray et al. and Pludow et al. the results in the comparison studies showed that in general, ForSys results were comparable to their MILP model in the single objective optimization problem. For instance, ForSys solved the largest problem (4300 stands) with 50 treatment blocks with a solution 2.37% less than the MILP model, and a solution times of 8 seconds versus in 1 hour. (Pludow et al. Table 2 bottom row). Murray et al. (2022) reported that the ForSys heuristic was found to be up to 6.69% less optimal (4.56% average across the 23 planning problems). The main issue regarding suboptimality was reported by Pludow et al. (2023) for a bi-objective problem. I acquired the same data w from the Stanislaus National Forests and was unable to replicate the outputs (Fig.4E, geographic unit 214 labeled as 1343 LMU in Pludow et al. (2023). It was also determined that treatment thresholds were not applied as specified in the SERAL management scenarios (Supplement Table S1), which would have a substantial effect on the solution since the Murray et al. model requires adjacency among treated stands to form a patch.

Further analysis of the problem, including documenting the small number of stands that could be aggregated to make an optimal treatment patch, and the relatively small number of stands in the overall problem reported in the comparison articles, motivated the testing of an alternative and simple GIS process where stand scale bi-objective scatter plots (Supplement Fig. S2) were used to find stands on the production frontier, and the threshold values for the two objectives were relaxed until stand aggregates of 100 acres or more appeared. This process yielded such a cluster from stands that were near optimal for both the ENVC and resiliency metrics (Supplement Fig. S2).

It is worth noting that six studies listed in the Pludow et al. (2023) compilation of ForSys studies (Vogler et al., 2015; Ager et al. 2017, 2019, 2021; Alcasena et al., 2018; Belavenutti et al., 2021) did not use the optimization heuristic, but rather pre-defined planning areas, and ForSys was used to sort the stands based on the objective value, treating those that exceeded a treatment threshold, until project scale constraints were met. This process identifies the exact optimal set of stands for each planning area.

3.2. Optimization for spatial planning problems in natural resource management

The larger discussion about the relative merits of mathematical programming formulations versus heuristics as applied in natural resource planning problems spans decades (see Schuster et al., 2020). Many of the early limitations with MILP for creating spatially compact or connected solutions have mostly been overcome with simpler methods for representing adjacency (Beyer et al., 2016; Hanson et al., 2023). With the many new solvers that have exponentially increased computational capacity (Harter et al., 2017; Gurobi Optimization, 2023, CPLEX, IBM, 2023), MILP and related MP formulations continue to be widely used as an experimental platform for spatial optimization problems in a wide range of resource planning problems (Garcia--Gonzalo and Borges, 2019; Duchardt et al., 2021). One common application is the optimization of fuel treatment arrangements to block the spread of wildfire or reduce intensity and hazard (Wei et al., 2008; Schroder et al., 2016; Borges et al., 2017; Ferreira et al., 2023). MILP is also widely employed in systematic conservation planning (Margules and Pressey, 2000; Schuster et al., 2019) and is rapidly replacing heuristics as the method of choice to design protected areas with platforms like Marxan (Schuster et al., 2020), Prioritzr (Hanson et al., 2023) as well as to prioritize ecological restoration (WePlan-Forests, IIS, 2024). In the case of Marxan, MILP produced superior solutions compared to the original simulated annealing heuristics (Beyer et al., 2016; Schuster et al., 2020). Superior solutions in this case are those that maximize the protection of biodiversity within conservation areas while minimizing cost of the acquired land. Schuster et al. (2020) appropriately qualifies that the recommendation for using MILP in conservation planning problems sis appropriate “where technical capacity exists”.

While it is beyond the scope of this paper to discuss all the technical advances and relative merits of new planning applications (see Schuster et al., 2020), including the MILP model presented in the comparison articles, the conclusion from this study is that the reported model formulations were developed to solve a different spatial planning problem than ForSys. Specifically, ForSys iteratively subdivides landscapes into discrete projects areas for implementation, building them one at a time with decreasing priority, based on how management actions can optimize one or more objectives. Projects are contiguous, not treated stands, and the final project size is determined by the interplay of a treatment threshold (if specified), the density of parcels that exceed that threshold, the objective contribution, and project scale activity constraint on total area treated. Connectivity is enforced by the heuristic since projects are built by adding adjacent stands, both treated and untreated. By contrast, the overall connectivity and compactness of solutions from platforms like Marxan and Prioritzr is achieved using global (the entire study area) penalties on metrics that describe compactness or boundary length of the selected parcels. For instance, Prioritizr uses two parameters to encourage clumped solutions, one being a boundary penalty that scales the importance of selecting polygons that are spatially clumped versus maximizing the overall objective (Supplement Fig. S3). The other parameter is an edge factor proportion that encourages the selection of stands that have selected neighbors. Using this approach, achieving a target treatment (or reserve selection) density that matches the operational environment is a trial and error process, and large planning areas (e.g., 10^6 ha) are not neatly partitioned into optimized project areas needed for US federal planning and operations (e.g., <20,000 ha). Thus replicating ForSys solutions would probably require pre-defined planning areas (Supplement Fig. S3), in which case an exact optimal solution can be found by simply sorting the stands as in Ager et al. (2021).

One key drawback to the application of MILP models that has not been discussed in prior papers is that their mathematical and operational complexity makes it difficult to communicate methods and solutions to non-technical stakeholders. Collaboration is increasingly common in US federal planning efforts and is mandated as part of legislation and agency policies (Schultz et al., 2012; Monroe and Butler, 2016; Coleman and Stern, 2018). Collaboration is explicitly required as a means of public engagement in the US Forest Service Planning Rule (USDA Forest Service, 2012). The planning and execution of land management projects on federal lands typically requires coordinated efforts across boundaries (USDA Forest Service, 2018) and among numerous and diverse stakeholder groups with the premise that on large multi-owner landscapes, acting collectively to reduce wildfire risk will have a better outcome than acting individually, or in an uncoordinated fashion (Charnley et al., 2020). Collaborative planning also can increase the probability that federal land management projects are not litigated by non-public entities (Summers, 2014). Although policies call for collaborative fuels planning to use the best available science (Colavito, 2017), conclusions from Colavito (2021) on barriers to implementation identified that communication about decision support systems (DSS) must be done in a common language and sustained through time to build relationships, and that DSS should be validated and tested with end users, and that end users need both education and training in the concepts and tools. Based on our research group's experience with ForSys and the numerous case studies (Day et al., 2023), planning platforms that employ mathematical programming methods cannot be widely implemented by field offices with current or future projected technical capacity. The author is unaware of any studies employing mathematical programming models that contributed to on-the-ground management decisions in recent history on US national forests. MILP models in particular were absent from the recent review of decision support tools used for forest management in fire frequent forests in the western US (Table4 in Colavito, 2021). By contrast, heuristics used by ForSys and many other optimization frameworks (Finney, 2004) are relatively easy to illustrate, explain and communicate to stakeholders (ForSys Research Consortium, 2024) as evidenced by their use in large landscape collaborative efforts in various western US states (New Mexico State Forestry, 2020, USDA Forest Service 2024).

Given the significant barriers to implementing MILP models for applied planning problems it is reasonable to ask if the operational cost of marginal improvements in optimality is worth slowing the wider adoption of spatial optimization tools, or is the continued research investment in MILP and related models required to find exact Pareto optima to solve real-world spatial planning problems. Empirical evidence that supports the wider use of heuristic-based optimization for project prioritization in the USFS was discussed in Ager et al. (2016) where ForSys was used to examine the optimality of prior projects already implemented by field units. The results showed that the ForSys heuristic was capable of identifying optimized treatment designs that substantially exceeded the objective values of implemented projects (Ager et al., 2016). This suggests that marginal suboptimality of a model that can be widely applied is not significant when its simplicity can lead to more widespread application on millions of hectares by public agencies tasked with allocating large investments for restoration and risk reduction treatments.

4. Summary and conclusions

The goal of this paper was to clarify the application and functionality of a decision support tool in use by the USFS, partner agencies, and non-governmental organizations to prioritize investments in restoration and risk reduction treatments in the Western US and elsewhere (New Mexico State Forestry, 2020, USDA Forest Service, 2022, 2024; Day et al., 2023). A secondary purpose was to provide broader perspective on the tradeoffs between MILP and heuristic approaches with a focus on operational needs in a large, decentralized agency like the USFS to prioritize management investments and understand tradeoffs. Both analytical solutions have advantages and limitations, and it is generally accepted that the method of choice is dependent on the complexity of the problem and the need for obtaining exact optimal solutions. In general, heuristics have the flexibility that allows adaptation to wide range of resource management problems and are a convenient choice when problems are not well defined and uncertainty is a significant factor. While greedy heuristics are computationally efficient and easy to implement, they may not always provide a perfectly optimal solution. From the examination of recent literature, and experience using both optimization methods as part research and field application, several conclusions can be made as follows.

1. While studies comparing the performance of heuristics versus MILP can provide important information to researchers and practitioners, robust comparisons need to carefully replicate the problem for which the models were designed, and report input parameters sufficient for others to replicate the analyses, especially those that affect optimality of solutions (see Schuster et al., 2020).
2. Based on the existing literature, researchers will continue to expand the application of mathematical optimization to solve spatial planning problems in natural resource conservation and management, both with and without adjacency constraints or objectives (Garcia-Gonzalo and Borges, 2019). A few recent examples include (Hirigoyen et al., 2021; Pascual et al., 2022; Wang et al., 2022; Carrasco et al., 2023; Rodrigues et al., 2021; Schuster et al., 2019). But the results will be specific for the study landscapes in terms of ecological conditions and respective disturbance regimes, and it appear that many of the models will remain in the research arena rather than serve end users tasked with regulatory planning problems on large landscapes.
3. There is a clear advantage to using heuristic-based optimization approaches when prioritization analyses are informing collaborative planning groups that require a high degree of transparency in the models and outputs.
4. I concur with the literature (Chazdon and Guariguata, 2018; Linkevičius et al., 2019) that complexity is the most significant barrier to the application of decision support tools in natural resource management, including those that employ spatial optimization methods. As summarized in Linkevičius et al. (2019), most decision support tools for forest management "are primarily designed by and for scientists and, that due to their complexity, they are generally considered not suitable for use in policy processes." This finding further supports the use of heuristics for applied problems related to prioritizing restoration and risk reduction investments.
5. Other than Land Tender (Vibrant Planet, 2023) and Planscape (2024), which are platforms developed specifically to replicate ForSys and incorporate the Patchmax heuristic, a planning system that currently replicates the functionality of ForSys was not apparent from the literature despite the recent appearance of several new platforms (Strassburg et al., 2020; Duchardt et al., 2021; IIS, 2024).

A significant issue observed in assessing various modeling platforms and associated publications related to ecosystem restoration and conservation (Zhang and Li, 2022; IIS, 2024) is the difficulty to measure how these applications are contributing to solving real-world management problems. For instance, how exactly are outputs translated to prioritization and decision support products? As an example, WePlan-Forests (IIS, 2024) has used MILP methods to prioritize conservation investments in tropical forests and has published results online for over 60 countries, constituting the most significant application of MILP technology to the biodiversity conservation problem. Similarly, Marxan has been used in a large number of conservation studies. The question is, how are these results being used by governance organizations in the landscapes analyzed in the model, and what barriers exist for using their results (Colavito, 2021)? It is suggested that a more systematic approach to evaluating models that include relevance to the management community is more important than finding exact optimal solutions.

Over time, incorporating uncertainty from climate change impacts on wildfire (Dupuy et al., 2020; Turco et al., 2023) and cascading effects on natural resource management issues will drive the need for novel planning systems to incorporate planning risk as part of prioritization (Polasky et al., 2011). The flexibility of heuristics as applied to the problem of prioritizing forest restoration and risk reduction investment will make them a framework of choice for these applications, especially those that are intended for field implementation. The relative ease with which heuristics can be developed and incorporated into optimization systems for planning problems and incorporating uncertainty surrounding future wildfire impacts may overwhelm technical arguments for exact optimality. Studies are lacking that incorporate stochastic wildfire into MILP models and thus uncertain wildfire impacts cannot be evaluated. By contrast, agent-based landscape models that employ simple heuristics to prioritize treatments and trigger wildfire events have been extensively used to understand future wildfire impacts

(Spies et al., 2017). In one of these, Barros et al. (2019) estimated that managers using risk metrics were only successful about 50% of the time in terms of identifying a project and implementing it before the area burned in a wildfire, thus representing a rare instance where planning risk (Polasky et al., 2011) has been examined in the context of future fire. These findings suggest that time is of the essence in terms of accelerating prioritization and implementation rather than investing effort in more complicated models to find exact optima.

CRediT authorship contribution statement

Alan Ager: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that he hase 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.

Acknowledgements

The author thanks Hugh Safford for comments on an earlier version of the manuscript and Michelle Day, Cody Evers, and Bruno Aparicio for technical assistance preparing supplementary material.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.121001.

References

Ager, A.A., Day, M.A., Vogler, K., 2016. Production possibility frontiers and socioecological tradeoffs for restoration of fire adapted forests. J. Environ. Manag. 176, 157–168. https://www.fs.usda.gov/research/treesearch/52994.

Ager, A.A., Evers, C.R., Day, M.A., Alcasena, F.J., Houtman, R., 2021. Planning for future fire: scenario analysis of an accelerated fuel reduction plan for the western United States. Landsc. Urban Plann. 215, 104212 https://doi.org/10.1016/j.landurbplan.2021.104212. https://www.fs.usda.gov/treesearch/pubs/63129.

Ager, A.A., Houtman, R., Day, M.A., Ringo, C., Palaiologou, P., 2019. Tradeoffs between US national forest harvest targets and fuel management to reduce wildfire transmission to the wildland urban interface. For. Ecol. Manag. 434, 99–109. https://www.fs.usda.gov/treesearch/pubs/57897.

Ager, A.A., Vaillant, N.M., Finney, M.A., 2011. Integrating fire behavior models and geospatial analysis for wildland fire risk assessment and fuel management planning. Journal of Combustion 572452, 19. https://doi.org/10.1155/2011/572452.

Ager, A.A., Vogler, K.C., Day, M.A., Bailey, J.D., 2017. Economic opportunities and trade-offs in collaborative forest landscape restoration. Ecol. Econ. 136, 226–239. https://www.fs.usda.gov/treesearch/pubs/54922.

Alcasena, F.J., Ager, A.A., Salis, M., Day, M.A., Vega-Garcia, C., 2018. Optimizing prescribed fire allocation for managing fire risk in central Catalonia. Sci. Total Environ. 4, 872–885. https://www.fs.usda.gov/research/treesearch/57191.

Ball, I.R., Possingham, H.P., 2000. MARXAN. v1.8.2: Marine Reserve Design Using Spatially Explicit Annealing.

Ball, I.R., Possingham, H.P., Watts, M., 2009. Marxan and relatives: software for spatial conservation prioritisation. In: Moilanen, A., Wilson, K.A., Possingham, H.P. (Eds.), Spatial Conservation Prioritisation: Quantitative Methods and Computational Tools. Oxford University Press, Oxford, pp. 185–210.

Barros, A.M.G., Ager, A.A., Day, M.A., Palaiologou, P., 2019. Improving long-term fuel treatment effectiveness in the National Forest System through quantitative prioritization. For. Ecol. Manag. 433, 514–527.

Belavenutti, P., Ager, A.A., Day, M.A., Chung, W., 2022. Designing forest restoration projects to optimize the application of broadcast burning. Ecol. Econ. 201, 107558. https://www.fs.usda.gov/research/treesearch/65117.

Belavenutti, P., Ager, A.A., Day, M.A., Chung, W., 2023. Multi-objective scheduling of fuel treatments to implement a linear fuel break network. Fire 6, 1. https://doi.org/10.3390/fire6010001.

Belavenutti, P., Chung, W., Ager, A.A., 2021. The economic reality of the forest and fuel management deficit on a fire prone western US national forest. J. Environ. Manag. 293, 112825. https://www.fs.usda.gov/treesearch/pubs/63130.

Beyer, H.L., Dujardin, Y., Watts, M.E., Possingham, H.P., 2016. Solving conservation planning problems with integer linear programming. Ecol. Model. 328, 14–22.

Borges, J.G., Marques, S., García-Gonzalo, J., Rahman, A.U., Bushenkov, V., Sottomayor, M., Carvalho, P.O., Nordstro, E.M., 2017. A multiple criteria approach for negotiating ecosystem services supply targets and forest owners' programs. For. Sci. 63, 49–61.

Brudvig, L.A., 2017. Toward prediction in the restoration of biodiversity. J. Appl. Ecol. 54, 1013–1017.

Cao, K., Li, W., Church, R., 2020. Big Data, Spatial Optimization, and Planning. SAGE Publications Sage UK, London, England, pp. 941–947.

Carrasco, J., Mahaluf, R., Lisón, F., Pais, C., Miranda, A., de la Barra, F., Palacios, D., Weintraub, A., 2023. A firebreak placement model for optimizing biodiversity protection at landscape scale. J. Environ. Manag. 342, 118087.

Charnley, S., Kelly, E.C., Fischer, A.P., 2020. Fostering collective action to reduce wildfire risk across property boundaries in the American West. Environ. Res. Lett. 15, 025007.

Chazdon, R.L., Guariguata, M.R., 2018. Decision Support Tools for Forest Landscape Restoration: Current Status and Future Outlook. Occasional Paper 183. Center for International Forestry Research, Indonesia.

Colavito, M., 2021. The human dimensions of spatial, pre-wildfire planning decision support systems: a review of barriers, facilitators, and recommendations. Forests 12, 483.

Colavito, M.M., 2017. Utilising scientific information to support resilient forest and fire management. Int. J. Wildland Fire 26, 375–383.

Coleman, K., Stern, M.J., 2018. Boundary spanners as trust ambassadors in collaborative natural resource management. J. Environ. Plann. Manag. 61, 291–308. https://doi.org/10.1080/09640568.2017.1303462.

Day, M.A., Ager, A.A., Houtman, R., Evers, C.R., 2023. Prioritizing Restoration and Risk Reduction Landscape Projects with the ForSys Planning System. Gen. Tech. Rep. RMRS-GTR-437. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO. https://doi.org/10.2737/RMRS-GTR-437.

Day, M.A., Houtman, R., Belavenutti, P., Ringo, C., Ager, A.A., Bassett, S., 2021. An assessment of forest and woodland restoration priorities to address wildfire risk in New Mexico. Gen. Tech. Rep. RMRS-GTR-423. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO. https://doi.org/10.2737/RMRS-GTR-423.

De Pellegrin Llorente, I., Hoganson, H.M., Carson, M.T., Windmuller-Campione, M., 2017. Recognizing spatial considerations in forest management planning. Current Forestry Reports 3, 308–316.

Dijkstra, E.W., 1959. A note on two problems in connexion with graphs. Numer. Math. 1, 269–271.

Duchardt, C.J., Monroe, A.P., Heinrichs, J.A., O'Donnell, M.S., Edmunds, D.R., Aldridge, C.L., 2021. Prioritizing restoration areas to conserve multiple sagebrush-associated wildlife species. Biol. Conserv. 260, 109212.

Dupuy, J.-l., Fargeon, H., Martin-StPaul, N., Pimont, F., Ruffault, J., Guijarro, M., Hernando, C., Madrigal, J., Fernandes, P., 2020. Climate change impact on future wildfire danger and activity in southern Europe: a review. Ann. For. Sci. 77.

Eaton, M.J., Yurek, S., Haider, Z., Martin, J., Johnson, F.A., Udell, B.J., Charkhgard, H., Kwon, C., 2019. Spatial conservation planning under uncertainty: adapting to climate change risks using modern portfolio theory. Ecol. Appl. 29, e01962 https://doi.org/10.1002/eap.1962.

Evers, C., Belavenutti, P., Day, M.A., Ager, A.A., Houtman, R., 2023a. patchmax: a spatial optimization package for building spatial priorities. Available at:, Version 0.2.0. https://github.com/forsys-sp/patchmax.

Evers, C., Houtman, R., Day, M.A., Belavenutti, P., Ager, A.A., 2023b. ForSysR: a scenario planning platform for modeling multi-criteria spatial priorities in R. Version R package version 0.9. Available at: https://github.com/forsys-sp/forsysr.

Ferreira, L., Nascimento Baptista, A., Constantino, M., Marques, S., Martins, I., Borges, J. G., 2023. Integrating wildfire resistance and environmental concerns into a sustainable forest ecosystem management approach. Frontiers in Forests and Global Change 6, 1177698. https://doi.org/10.3389/ffgc.2023.1177698.

Finney, M.A., 2004. Chapter 9, landscape fire simulation and fuel treatment optimization. In: Hayes, J.L., Ager, A.A., Barbour, J.R. (Eds.), Methods for Integrated Modeling of Landscape Change: Interior Northwest Landscape Analysis, System, pp. 117–131. US Forest Service Gen. Tech. Rep., PNW-GTR-610. Portland, Oregon. 218. http://www.firemodels.org/downloads/flammap/publications/Finney_2004_PNW-GTR-610_INLAS.pdf.

ForSys Research Consortium, 2024. The ForSys Research Consortium. www.forsysplanning.org.

Garcia-Gonzalo, J., Borges, J.G., 2019. Models and tools for integrated forest management and forest policy analysis: an Editorial. For. Pol. Econ. 103, 1–3.

Gurobi Optimization, L., 2023. Gurobi Optimizer Reference Manual. Version. Available at: https://www.gurobi.com.

Hanson, J., Schuster, R., Morrell, N., Strimas-Mackey, M., Edwards, B., Watts, M., Arcese, P., Bennett, J., Possingham, H., 2023. Prioritizr: systematic conservation prioritization in R. Version. Available at: https://prioritizr.net https://github.com/prioritizr/prioritizr.

Harter, R., Hornik, K., Theussl, S., Szymanski, C., Schwendinger, F., Hornik, M.K., 2017. Package 'Rsymphony'.

Hessburg, P.F., Reynolds, K.M., Keane, R.E., Salter, R.B., 2006. A multi-scale decision support system for evaluating wildland fire hazard and prioritizing treatments. In: Proceedings of the 3rd International Fire Ecology and Management Congress. November 13-17, 2006, San Diego, CA.

Hirigoyen, A., Acuna, M., Rachid-Casnati, C., Franco, J., Navarro-Cerrillo, R., 2021. Use of optimization modeling to assess the effect of timber and carbon pricing on harvest scheduling, carbon sequestration, and net present value of Eucalyptus plantations. Forests 12, 651.
IBM, 2023. CPLEX. Version. Available at: https://www.ibm.com/products/ilog-cplex-optimization-studio/cplex-optimizer.
Iftekhar, M.S., Polyakov, M., Ansell, D., Gibson, F., Kay, G., 2017. How economics can further the success of ecological restoration. Conserv. Biol. 31, 261–268. https://doi.org/10.1111/cobi.12778.
IIS, 2024. WePlan forests: forest restoration planning. http://weplan-forests.org/index.html.
Kukkala, A.S., Moilanen, A., 2013. Core concepts of spatial prioritisation in systematic conservation planning. Biol. Rev. 88, 443–464.
Linkevičius, E., et al., 2019. Linking forest policy issues and decision support tools in Europe. For. Pol. Econ. 103, 4–16.
Margules, C.R., Pressey, R.L., 2000. Systematic conservation planning. Nature 405, 243–253.
Monroe, A.S., Butler, W.H., 2016. Responding to a policy mandate to collaborate: structuring collaboration in the collaborative forest landscape restoration program. J. Environ. Plann. Manag. 59, 1054–1072.
Murray, A.T., Church, R.L., 2023. Spatial optimization of multiple area land acquisition. Comput. Oper. Res. 153, 106160 https://doi.org/10.1016/j.cor.2023.106160.
Murray, A.T., Church, R.L., Pludow, B.A., Stine, P., 2022. Advancing contiguous environmental land allocation analysis, planning and modeling. J. Land Use Sci. 17, 572–590.
New Mexico State Forestry, 2020. The forest action plan. http://www.emnrd.state.nm.us/SFD/statewideassessment.html.
Noss, R., Nielsen, S., Vance-Boland, K., 2009. Chapter 12 – prioritizing ecosystems, species and sites for restoration. In: Moilanen, A., Wilson, K.A., Possingham, H.P. (Eds.), Spatial Conservation Prioritization: Quantitative Methods and Computational Tools. Oxford University Press, Oxford, pp. 158–170.
Pascual, A., Giardina, C.P., Povak, N.A., Hessburg, P.F., Heider, C., Salminen, E., Asner, G.P., 2022. Optimizing invasive species management using mathematical programming to support stewardship of water and carbon-based ecosystem services. J. Environ. Manag. 301, 113803.
Peterson, G.D., Cumming, G.S., Carpenter, S.R., 2003. Scenario planning: a tool for conservation in an uncertain world. Conserv. Biol. 17, 358–366.
Planscape, 2024. Planscape: a planning tool to maximize wildfire resilience and ecological benefits. https://www.planscape.org/.
Pludow, B.A., Murray, A.T., Echeverri, V., Church, R.L., 2023. Evaluation of forest treatment planning considering multiple objectives. J. Environ. Manag. 346, 118997. https://www.ncbi.nlm.nih.gov/pubmed/37769367.
Pohjanmies, T., Eyvindson, K., Mönkkönen, M., 2019. Forest management optimization across spatial scales to reconcile economic and conservation objectives. PLoS One 14, e0218213.
Polasky, S., Carpenter, S.R., Folke, C., Keeler, B., 2011. Decision-making under great uncertainty: environmental management in an era of global change. Trends Ecol. Evol. 26, 398–404.
Reynolds, K.M., 2001. EMDS: using a logic framework to assess forest ecosystem sustainability. J. For. 99, 26–30. http://www.ingentaconnect.com/content/saf/jof/2001/00000099/00000006/art00006.
Riddell, G.A., van Delden, H., Maier, H.R., Zecchin, A.C., 2019. Exploratory scenario analysis for disaster risk reduction: considering alternative pathways in disaster risk assessment. Int. J. Disaster Risk Reduc. 39, 101230 https://doi.org/10.1016/j.ijdrr.2019.101230.
Rodrigues, A.R., Marques, S., Botequim, B., Marto, M., Borges, J.G., 2021. Forest management for optimizing soil protection: a landscape-level approach. Forest Ecosystems 8, 1–13.
Schroder, S.A.K., Tóth, S.F., Deal, R.L., Ettl, G.J., 2016. Multi-objective optimization to evaluate tradeoffs among forest ecosystem services following fire hazard reduction in the Deschutes National Forest, USA. Ecosyst. Serv. 22, 328–347.
Schultz, C.A., Jedd, T., Beam, R.D., 2012. The collaborative forest landscape restoration program: a history and overview of the first projects. J. For. 110, 381–391.
Schuster, R., Hanson, J.O., Strimas-Mackey, M., Bennett, J.R., 2020. Exact integer linear programming solvers outperform simulated annealing for solving conservation planning problems. PeerJ 8, e9258. https://doi.org/10.7717/peerj.9258.
Schuster, R., Wilson, S., Rodewald, A.D., Arcese, P., Fink, D., Auer, T., Bennett, J.R., 2019. Optimizing the conservation of migratory species over their full annual cycle. Nat. Commun. 10, 1754.
Spies, T., et al., 2017. Using an agent-based model to examine forest management outcomes in a fire-prone landscape in Oregon, USA. Ecol. Soc. 22, 25. https://doi.org/10.5751/ES-08841-220125.
Strassburg, B.B., Iribarrem, A., Beyer, H.L., Cordeiro, C.L., Crouzeilles, R., Jakovac, C.C., Braga Junqueira, A., Lacerda, E., Latawiec, A.E., Balmford, A., 2020. Global priority areas for ecosystem restoration. Nature 586, 724–729.
Summers, B.M., 2014. The Effectiveness of Forest Collaborative Groups at Reducing the Likelihood of Project Appeals and Objections in Eastern Oregon.
Turco, M., Abatzoglou, J.T., Herrera, S., Zhuang, Y., Jerez, S., Lucas, D.D., AghaKouchak, A., Cvijanovic, I., 2023. Anthropogenic climate change impacts exacerbate summer forest fires in California. Proc. Natl. Acad. Sci. USA 120, e2213815120.
USDA Forest Service, 2012. National Forest System Land Management Planning Rule, 0596–AD0502 36 CFR Part 219.
USDA Forest Service, 2018. Towards Shared Stewardship across Landscapes: an Outcome-Based Investment Strategy. FS-118. USDA Forest Service, Washington, DC.
USDA Forest Service, 2022. Confronting the Wildfire Crisis: A Strategy for Protecting Communities and Improving Resilience in America's Forests. FS-1187a, Washington D.C.
USDA Forest Service, Stanislaus National Forest, 2021. Appendix E. Using Landscape Condition Metrics and ForSys for the Social and Ecological Resilience across the Landscape Project. Draft Environmental Impact Statement Stanislaus National Forest 56500. Sonora, CA.
USDA Forest Service, Stanislaus National Forest, 2024. Social and ecological resilience across the landscape (SERAL). https://www.fs.usda.gov/project/?project=56500.
Vibrant Planet, 2023. Land Tender: a platform for landscape restoration. https://www.vibrantplanet.net/landtender.
Vogler, K.C., Ager, A.A., Day, M.A., Jennings, M., Bailey, J.D., 2015. Prioritization of forest restoration projects: tradeoffs between wildfire protection, ecological restoration and economic objectives. Forests 6, 4403–4420. https://www.fs.usda.gov/treesearch/pubs/52992.
Wang, Y., Qin, P., Önal, H., 2022. An optimisation approach for designing wildlife corridors with ecological and spatial considerations. Methods Ecol. Evol. 13, 1042–1051.
Wei, Y., Rideout, D., Kirsch, A., 2008. An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. Can. J. For. Res. 38, 868–877.
Zhang, L., Li, J., 2022. Identifying priority areas for biodiversity conservation based on Marxan and InVEST model. Landsc. Ecol. 37, 3043–3058.