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# Designing forest restoration projects to optimize the application of broadcast burning

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ABSTRACT

Active forest restoration programs on western US national forests face multiple challenges to meet their broad ecological goals while designing projects that generate sufficient revenue to build and maintain private forest management capacity needed to expand the scale and scope of treatments. We explored ways to design projects where admixing of treatments along gradients of dry and moist mixed conifer forest types could maximize financial viability while including substantial area where broadcast burning could be applied in conjunction with other treatments. In general, we found that restoration treatments in dry forests that included density reduction thinning and broadcast burning resulted in a net projected cost ranging from $110 to $8000 per ha. By contrast, density reduction thinning in moist mixed conifer forests on more productive microsites generated significant commercial timber volume and projected revenue that ranged from $4000 to $20,000 per ha. We used spatial optimization methods to identify potential project areas that maximized revenue while meeting constraints to treat a minimum proportion of each project with broadcast burning. Multiple project area sizes were also explored to understand the effect of restoration scale on financial outcomes. We found that optimal projects in terms of generating revenue to subsidize density reduction and broadcast burning were 810 ha and contained >50% dry forest area. Larger projects and those with a higher percentage of dry forest area resulted in lower revenue, eliminating revenue when projects reached 2700 ha. Forest restoration programs can use these methods to plan and design restoration projects that are financially viable while addressing the broadcast burn backlog in dry forests that require relatively expensive fuel reduction treatments prior to re-introducing fire.

## 1. Introduction

Active restoration management on federal lands in the western US aims to restore the natural and historical patterns of forest structure, composition, and underlying natural disturbance regimes (Hessburg et al., 2016). Federal policy deems that restoration management applies to the full range of fire regimes and forest types from arid juniper woodlands (Miller et al., 2014), dry pine (Hessburg et al., 2005), moist mixed conifer (Hessburg et al., 2016; Stine et al., 2014), and cold subalpine forests (Tomback et al., 2022). Despite the wide range of ecological conditions where restoration activities are applied, the bulk of investments are allocated to widespread dry pine and mixed conifer forests. In the former, restoration goals are to restore fire resiliency and maintain them with broadcast burning and naturally ignited wildfires (Huffman et al., 2020; Kolden, 2019; Stephens et al., 2021). In the latter, where fire return intervals are longer and characterized by mixed severity fire, restoration goals are to create successional mosaics of different forest types that limit patch size of high severity fire, and restore stand density and structure to presettlement conditions that conferred adaptation to fire, drought, insects and disease, and resilience to climate change (Hessburg et al., 2015; Stine et al., 2014). Although the objectives are different, broadly similar silvicultural and fuel treatment methods and guidelines are applied with the notable exception that broadcast burning is not practiced in moist mixed conifer stands since these species are less fire tolerant (Stine et al., 2014).

Despite the well described restoration goals, stand prescriptions for mechanical and prescribed fire treatments (Jain et al., 2012), and national priority maps (Butler et al., 2015), optimizing the design of individual project areas within which restoration treatments are allocated is less well studied. Project boundaries in montane western US national

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forests are typically aligned along watershed boundaries and often, but not always, enclose ecological mosaics of natural fire regimes that follow fine-scaled gradients in soils, aspect, moisture and related environmental conditions (Hessburg et al., 2015). However, the selection of watershed-scale projects and specific boundaries for enclosing them are repeatedly adjusted by planners using ad hoc methods to optimize localized restoration need and opportunity, and enhance ecological, fire management, and financial outcomes. In general, locating priority landscapes and identifying project boundaries is a balancing act between the opportunity to restore low severity fire in dry forest stands (fire regimes I and III (LANDFIRE, 2017)), versus addressing more complicated forest health and fire management objectives in the mosaic of moist mixed conifer in the same project area. Finding the correct balance is important to restoration programs because, in general, treatments in the former are costly and rarely balanced by the revenue from small diameter trees generated from density reduction thinning, whereas in the latter, substantial commercial volume can be generated from the more productive forest stands (Belavenutti et al., 2021). In effect, admixing diverse forest types into a single project can substantially improve financial suitability for contractors to perform restoration treatments while addressing fire resiliency goals in dry forests (USDA Forest Service, 2018). Moreover, commercial timber and biomass materials are also critical economic outputs to sustain rural economies consistent with the mission of the US Forest Service (USDA Forest Service, 2017), resulting in a mix of forest types to generate revenue.

Although there are a number of studies that include some aspects of prioritizing forest management, and specifically restoration projects (Ager et al., 2016; Florec et al., 2020; Minas et al., 2014; Schroder et al., 2016; Williams et al., 2017), the bulk of these models measure benefits in terms of reduced fire risk to ecosystem services (Schroder et al., 2016), or more direct measures of wildfire hazard or risk to the wildland-urban interface (Addington et al., 2020; Hmielowski et al., 2016), rather than examine financial considerations that are arguably the main constraint to expanding the space and scale of treatments, especially in areas where dry pine forests are the dominant restoration target (Ager et al., 2021a; Hjerpe et al., 2009). Other studies have focused entirely on broadcast burning (Addington et al., 2020; Alcasena et al., 2018; Rachmawati et al., 2015) and thus do not consider the co-prioritization of mechanical treatments that are interdependent with fire in terms of ecological, financial, and risk outcomes (Agee and Skinner, 2005; Jain et al., 2012).

Given the importance of both economics and fire ecology to achieve restoration goals on western US national forests, we used a spatial optimization model to examine how projects could be containerized to maximize revenue from thinning treatments while including significant areas of treatment in dry forests that are needed to re-introduce broadcast burning. The study area was a 357,000-ha national forest in the interior Pacific Northwest where restoration management faces multiple challenges to address the fire deficit and stand densification. We simulated project design scenarios that maximized revenue while meeting minimum constraints for the area of dry forest stands that can receive broadcast burning treatments once mechanical treatments are completed. The simulations led to the identification of specific project areas and treatment designs that both generated revenue from density reduction treatments in primarily mixed conifer stands while co-locating specific levels of broadcast burning treatments in dry forests within the same planning area. The modeling approach provides a practical method for optimally admixing different forest ecological settings in the process of designing financially viable restoration projects that address the backlog of prescribed fire in many western US national forests.

## 2. Study area

The study area (Fig. 1) is part of the Umatilla National Forest (Umatilla NF) in the Blue Mountain ecoregion (USDA Forest Service, 1994) in northeast Oregon and southeast Washington in the US. The

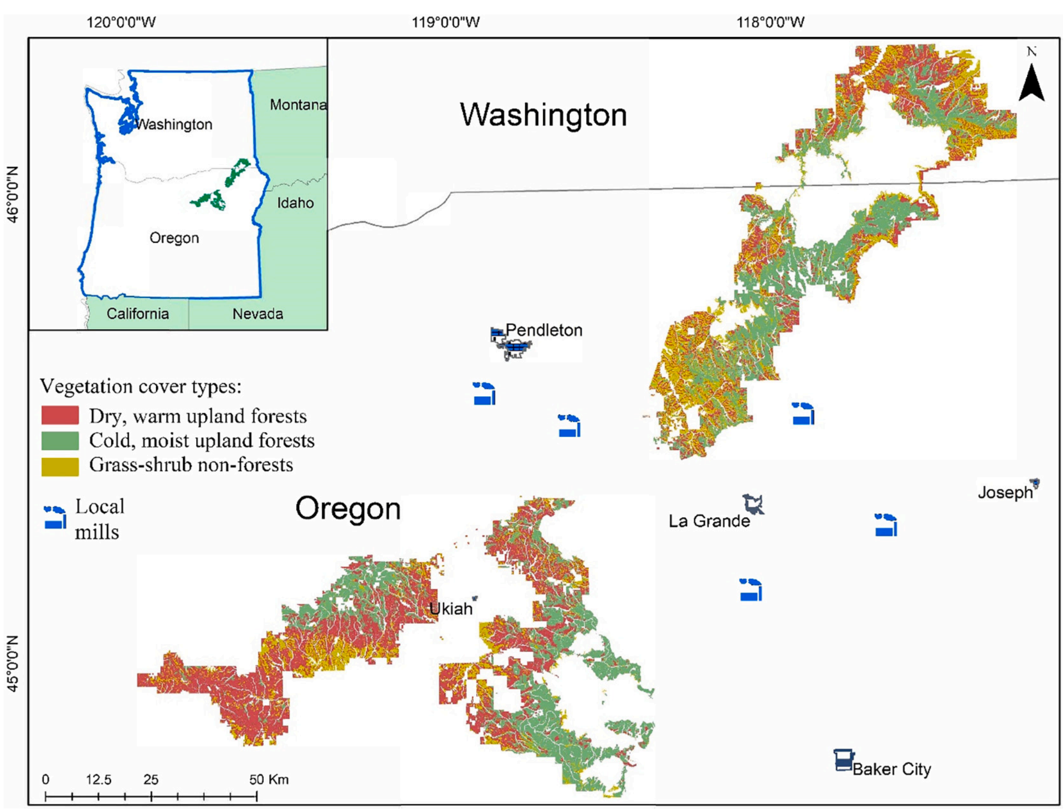


**Fig. 1.** Vegetation classes across the study area for stands available for active management on the Umatilla National Forest (USDA Forest Service, 1990), and location of nearest mills.

Umatilla NF is about 520,000 ha in size, with elevations ranging from 500 m to 1500 m, with the highest peaks close to 2300 m. The vegetation is characterized by mixed dry and warm forests with different dominant species, mainly ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson) at lower elevations, and dry mixed conifer (grand fir (*Abies grandis* (Douglas ex D. Don) Lindl) and Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco)) at higher elevations. Cold and moist forests are found at mid to high elevations dominated by lodgepole pine (*Pinus contorta* Douglas ex Loudon).

The analysis was conducted on 356,942 ha designated for active management excluding special management designation areas (i.e., wilderness, research natural areas, inventoried roadless areas, experimental forest and riparian habitats) and non-vegetated areas (i.e., rock, water, etc.) (USDA Forest Service, 2016). The stand layer was obtained from the Umatilla NF with stand boundaries following natural breaks in vegetation type and changes in stand structure from past management activities. Stand inventories were obtained from corporate USDA Forest Service spatial databases. Each forested stand was attributed with data on biological groupings (biogroups) which were based upon upland forest Plant Association Groups (Appendix A Table A1). Differences among biogroups are related to moisture and temperature gradients within the study area. For those having a Plant Association Group of cool to cold these were assigned to biogroup 1, 2 or 3. Hot to warm or warm moist plant association groups were assigned to biogroups 4, 5 and 6. A total of 46,929 non-forested and forested stands in the study area are available for restoration treatments, ranging in size from 1 ha to 300 ha with an average of 7.5 ha. Cold and moist forest stands (biogroups 1–3) in the study area cover 127,905 ha (36%), dry and warm forest stands (biogroups 4–6) cover 139,695 9 ha (39%) and grass-shrub areas cover 110,592 ha (25%).

### 2.1. Stand treatment assignment

Stand attribute thresholds and local knowledge about current silvicultural practices defined the suitable treatments (Table 1). Prescriptions formulated for sequences of restoration treatments included mechanical thinning and surface fuels treatments that replicate strategies on the Umatilla NF. We modeled stand prescriptions using the Forest Vegetation Simulator (FVS) Blue Mountains variant (Keyser and Dixon, 2015). Stands available for thinning treatments were filtered based on thresholds for maximum stand density index (SDI, Cochran et al., 1994). If SDI exceeded 55% of the maximum SDI for stands within the corresponding site capacity, we simulated a thinning from below to achieve a post-thin stocking of 30% of the maximum SDI. Thinning from below prioritized removal of smaller trees of fire-intolerant species (e.g., grand fir) and reduced ladder fuels to prevent torching and crowning fire behavior. The maximum tree size for harvest was set at 53.3 cm diameter at breast height (DBH) to meet late-old structure (LOS) objectives as specified in local harvest guidelines (USDA and USDI, 1994). Dry warm mixed conifer stands (hereafter dry forest stands) were assigned to receive broadcast burn treatment and cold moist stands were assigned to pile & burn treatment. Pile & burn is to burn hand or machine piles of cut vegetation from fuels management activities (Jain et al., 2012). Non-forested stands of grass-shrub lands were assigned to receive a broadcast burn treatment.

**Table 1**
Stand thresholds used to determine treatment types (from Belavenutti et al. (1)).

| Threshold | Treatment Types |
|---|---|
| Stand density index (SDI) >55% of maximum SDI | Available for thinning |
| Merchantable volume > 35 $m^3$ $ha^{-1}$ | Commercial thinning |
| Thinning volume > 0 $m^3$ $ha^{-1}$ and < 35 $m^3$ $ha^{-1}$ | Non-commercial thinning (density reduction) |
| Pre-treatment = non- and commercial thin AND forest type = dry, warm upland forest | Thin + Broadcast burn (2 years post-thinning) |
| Pre-treatment = non- and commercial thin AND forest type = cold, moist forest AND fuel loading >3.6 ton $ha^{-1}$ in the 0–7.6 cm diameter size class | Thin + Pile & burn (2 years post-thinning) |
| Post-fire tree mortality <50% for trees larger than DBH of 22.8 cm and > 50% for trees smaller than DBH of 7.6 cm AND forest type = dry, warm upland forest | Broadcast burn only |
| Fuel loading >3.6 ton $ha^{-1}$ in the 0–7.6 cm diameter size class AND forest type = cold, moist forest | Pile & burn only |
| Thresholds for treatments do not apply (e.g., stand received treatment in last 15 years) | Broadcast burn only |
| Stand is grass-shrub non-forest | Broadcast burn only |

### 2.2. Financial valuation

Parameters for costs and revenue were obtained from local transaction data on the Umatilla NF. We did not consider extraneous project implementation costs such as road re-construction or decommissioning or planning costs. We used the economic extension of FVS to convert modeled harvest volume outputs into logs of specific size and species (Martin, 2013). Corresponding average pond values ($ $m^{-3}$) ranging from $71 to $101 were collected from timber sale specialists on the Umatilla NF and used to calculate the total value of delivered logs from each stand. Log pond values were only calculated for stands that generated >35 $m^3$ $ha^{-1}$ of merchantable timber, assuming stands producing less were not commercially viable.

Harvest costs ($ $m^{-3}$) ranging from $10 to $110 were calculated based on slope and tree size class consistent with methods used in previous studies (Rainville et al., 2008; Rummer, 2008). A ground-based harvesting system was assigned for stands having a slope ≤ 35%, and a cable harvesting system was assigned for all stands that exceeded the 35% threshold. Average slope per stand was calculated from digital elevation data with a resolution of 30 m.

Timber hauling costs from individual stands to the nearest wood processing facility were estimated using the road network data for the study area. The road network consisted of approximately 750,000 road sections which were classified by driving speed. Round-trip travel time between each stand and the nearest processing facility was computed for the shortest path using travel distance and speed (Dijkstra, 1959). One additional hour of delay time was added for loading, unloading and wait times. Round trip costs per one cubic meter of timber were then estimated using travel time, truck hourly cost of $100, and truck load capacity of 12 $m^3$.

If thinning was not commercially viable (i.e., volume removal <35 $m^3$ $ha^{-1}$), it was assumed to be a non-commercial thinning incurring costs of $1600 $ha^{-1}$. The costs of pile & burn and broadcast burn were assumed to be $1110 $ha^{-1}$ and $110 $ha^{-1}$, respectively.

### 2.3. Simulated restoration scenarios

We simulated 16 restoration scenarios to assess the economic effects of varying project size and the percentage of dry forest area available to treat within the project (Table 2). Each scenario simulated a specific number of projects to treat a total of ca. 32,400 ha across the Umatilla NF (about 8% of the active management area), matching the Forest's capacity over a 4–5-year implementation horizon. Project sizes between 810 and 4050 ha were defined by Umatilla NF staff and ranged in size according to similar projects implemented by the Forest in the last few years with ±10% tolerance (e.g., projects could fall short of the target area by up to 10%). The minimum dry forest area within projects simulated was 0, 25, 50 and 75%.

### 2.4. Stand aggregation for project areas

We developed a new spatial module in R (R package *Patchmax* Appendix B) for forest stand aggregation, and incorporated it into the ForSysR program (Ager et al., 2021b; Belavenutti et al., 2021) to build and identify efficient project areas for a given objective across a large

**Table 2**
Simulated scenarios and associated number of projects, project size and minimum percentage of dry forest.

| Scenario | Project size (ha) | Minimum dry forest area (%) | Number of projects |
|---|---|---|---|
| 1 | 810 | 0 | 40 |
| 2 | 810 | 25 | 40 |
| 3 | 810 | 50 | 40 |
| 4 | 810 | 75 | 40 |
| 5 | 1620 | 0 | 20 |
| 6 | 1620 | 25 | 20 |
| 7 | 1620 | 50 | 20 |
| 8 | 1620 | 75 | 20 |
| 9 | 2700 | 0 | 12 |
| 10 | 2700 | 25 | 12 |
| 11 | 2700 | 50 | 12 |
| 12 | 2700 | 75 | 12 |
| 13 | 4050 | 0 | 8 |
| 14 | 4050 | 25 | 8 |
| 15 | 4050 | 50 | 8 |
| 16 | 4050 | 75 | 8 |

landscape. The module employs a graph theory algorithm called breadth-first search (BFS, Cormen et al. (2015)) from the igraph software package (Csardi and Nepusz, 2006), and couples it with iterative search and parallel programming to rapidly explore adjacent forest stands from a given start location (i.e., a root stand) and build a project area candidate of desirable size. During the first iteration, the module runs the search algorithm on *n* available stands in a given landscape considering each of the stands as a root (Fig. 2). This process generates *n* project area candidates, which are then evaluated for a given objective function and constraint. Among all feasible candidates, the best performing project area is selected and stored. The next iteration begins after the best project area selected from the previous iteration is removed from the landscape so that none of the stands in the previously selected project areas can serve as a root or be included in a new project area. The search algorithm repeats until a desired number of project areas is met. The user supplies a restoration scenario in terms of objectives (e.g., maximize net revenue) and constraints (e.g., project area size, dry forest proportion), and the optimization module identifies the best project areas for the given objective and constraints.

The *Patchmax* module uses Eqs. 1 through 4 to evaluate the quality and feasibility of project candidates. Eq. 1 is used to calculate the total objective value of each project candidate, *p* (net revenue in this study). Eqs. 2 and 3 are the project area treatment constraints that allow a min and *max* proportional deviation from the project area target (±10% in our scenarios). Eq. 4 specifies additional constraints on area treated specific to a stratum within each project. Strata could be defined by dry forest (as in this study), old growth, wildlife habitat or any other characteristics. The constraint ensures a minimum proportion of area of the specified strata are treated as part of the solution for each project area.

$$Z = \sum_{j=1}^{kp} c_j x_{jp} \tag{1}$$

$$\sum_{j=1}^{kp} a_j x_{jp} \leq \Delta_{max} Prj_{area} \tag{2}$$

$$\sum_{j=1}^{kp} a_j x_{jp} \geq \Delta_{min}\, Prj_{area} \tag{3}$$

$$\sum_{j=1}^{kp} \left(a_j x_{jp\in\delta(Dp)}\right) \geq Prop\_stratum_k \times Prj_{area} \tag{4}$$

Where *kp* is the total number of available stands in the study area for project *p*, *x* is a binary vector indicating whether the $j^{th}$ stand is treated in project *p* ($x_{jp} = 1$) or not ($x_{jp} = 0$), $c_j$ is the net revenue contribution of stand *j* if treated, $a_j$ is the area of the $j^{th}$ stand, $Prj_{area}$ is the project area target, $\Delta_{max}$ and $\Delta_{min}$ are the maximum and minimum proportional deviation from that target, $\delta(Dp)$ is the set of stands belonging to $stratum_k$ within project *p*, and *Prop_stratum* is the minimum required proportion of the *stratum* between 0 and 1.0. We used a server computer equipped with two Intel® Xenon® Gold 6152 processors with 2.10 GHz and 44 cores to run the *Patchmax* module with average solution times <5 s per project.

### 2.5. Simulation outcome analysis

We performed a sensitivity analysis to explore the impact of project area size and percentage of dry forest area on the financial performance and spatial distribution of restoration projects across the Umatilla NF. The cumulative effects of treatments on net revenue were also analyzed to identify the area in each scenario that can be treated with and without external investment. We also developed project implementation schedules for each scenario, assuming that projects are implemented in the order of highest net revenue for the next 5 years. Net revenue was standardized to year 3 of the planning horizon with a 1% interest rate. We demonstrate project scheduling with two scenario examples that include a high percentage of dry forest but differ in the need for external investment to complete restoration.

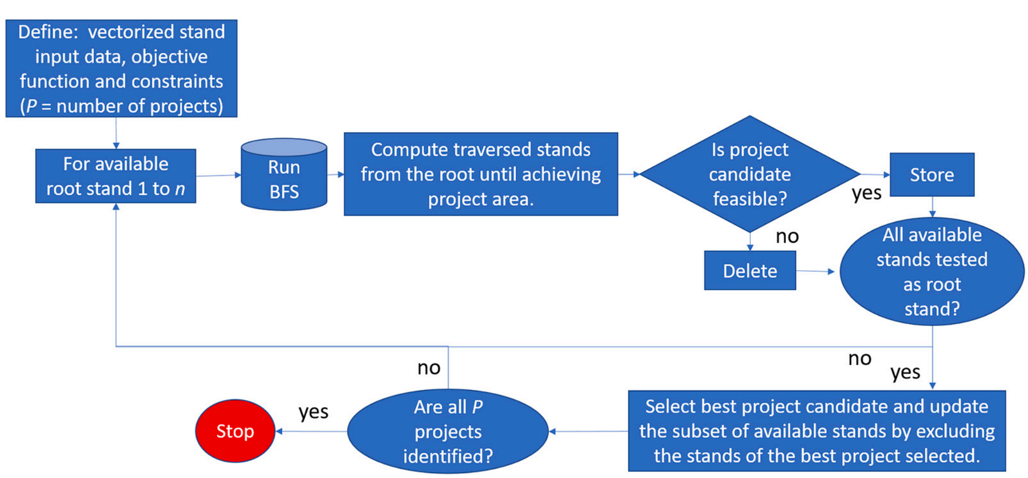


**Fig. 2.** Decision logic of *Patchmax*. In each iteration, the algorithm generates a large number of project candidates using the breadth-first search (BFS) algorithm while considering each available stand as a root of the project area. It then identifies the best project area among all feasible candidates for a given objective function. The process repeats until the user-defined number of project areas is reached.

## 3. Results

### 3.1. Restoration scenarios

The results showed that project areas were selected in each scenario to admix revenue generating treatments (i.e., commercial thinning) with cost incurring restoration treatments (i.e., non-commercial thinning/density reduction or fuels reduction treatments), while meeting the given project size and dry forest constraints. All restoration scenarios generated the required number of project areas except for the scenario with the largest projects and the highest dry forest percentage (Scenario 16; Table 3). In this scenario, the search algorithm was not able to find more than six project areas that met both the given project size and dry forest percentage constraints due to the lack of large contiguous areas with dry forest stands. The total net revenue of each scenario ranged widely from -\$20.8 million to \$19.9 million. In general, the more commercial thinning treatments were included, the higher the net revenue generated. When ≥75% of dry forest area was required (i.e., Scenarios 4, 8, 12 and 16), net revenue decreased substantially because the project locations shifted dramatically toward dry forest stands (Appendix A Fig. A1) where many areas were in need of density reduction.

Fig. 3 illustrates an example of selected project areas where revenue generating commercial thinning was blended with other cost incurring fuels treatments to scale up restoration. The two adjacent project areas shown in Fig. 3 came from Scenario 6, treating 3235 ha with 42% of the treatment area being dry forest. The two projects included about 500 ha of commercial thinning from both cold moist and warm dry forests (areas in dark red and dark blue in Fig. 3), generating a positive net revenue of \$2.9 million. This revenue was used to provide financial assistance for over 2600 ha of other fuels treatments including 44% warm dry forest stands, 41% cold moist stands and 15% non-forested stands.

### 3.2. Sensitivity analysis

The selection of individual restoration projects and their financial performance varied with project size and dry forest constraint. Fig. 4 shows net revenue of individual projects ranked in order from the highest to the lowest in each scenario. The net revenue of a single project ranged from -\$2.5 million to \$3.5 million. The number of positive net revenue projects varied highly based on dry forest percentage. With no dry forest requirement, most projects were able to generate positive net revenue (i.e., Scenarios 1, 5, 9 and 13). The number of positive net revenue projects dropped quickly when dry forest percentage increased, especially when >50% of the project area was required to be dry forest. This is because more profitable commercial thinning in cool, moist forests had to be replaced by less profitable dry forest treatments. This decreasing trend of net revenue with more dry forest was accelerated further with larger projects due to the scarcity of large contiguous areas that included highly profitable dry forest stands. For example, the combination of >50% dry forest and projects >2000 ha resulted in only a single revenue-generating project.

### 3.3. Spatial distribution of restoration projects

The dry forest constraint dramatically changed the location of selected restoration projects in each scenario. Fig. 5 shows the project areas where project size was constrained around 2700 ha, but with different dry forest percentage constraints (Scenarios 9 through 12). With no or low dry forest requirement (i.e., 0% or 25% minimum dry forest, Fig. 5), all of the selected projects were located in the northeastern portion of the study area, where cold, moist forests are concentrated. At the 50% dry forest constraint, some project areas started appearing in the southwestern portion of the study area where dry, warm forests predominate. At a minimum 75% dry forest constraint, most project areas shifted to the southwestern portion of the study area.

### 3.4. Financial position and investment needs

Dry forest and project size constraints affected not only the spatial location of individual projects, but also the financial position and investment needs of the projects. Fig. 6 shows the cumulative effect of treatment area on net revenue in each restoration scenario. Projects generally perform financially better with no or minimal constraints because of increased flexibility to identify highly profitable treatment locations, such as commercial thinning in cold, moist forests. Our analysis showed that all project areas in the scenarios with no or 25% dry forest constraint could produce a budget surplus regardless of project size (Scenarios 1, 2, 5, 6, 9, 10, 13, 14). When dry forest constraint increased to 50%, only the scenario with the smallest project size (Scenario 3, project size constraint = 810 ha) resulted in positive net revenue, thus avoiding external investment. When the dry forest constraint further increased to 75%, three scenarios with project sizes of 1620 ha or above (Scenarios 8, 12, 16) had no single project that could be implemented without external investment (Fig. 6).

### 3.5. Project scheduling

We selected two sample scenarios (Scenarios 3 and 12) to

**Table 3**
Constraints and treatment results for the sixteen scenarios varying project size and percentage of dry forest.

| Scenario | Number of projects | Average project size (ha) | Dry forest area (%) | Total net revenue (\$ million) | Treatment area (ha) | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Commercial thinning | Non-commercial thinning | Broadcast burn | Pile & burn |
| 1 | 40 | 834 | 31 | 19.9 | 7136 | 5869 | 19,762 | 6476 |
| 2 | 40 | 847 | 43 | 14.4 | 5037 | 4482 | 25,199 | 3640 |
| 3 | 40 | 902 | 66 | 1.6 | 2475 | 3412 | 31,974 | 1626 |
| 4 | 40 | 861 | 82 | −10.9 | 2399 | 8418 | 31,385 | 659 |
| 5 | 20 | 1671 | 32 | 14.3 | 6004 | 5912 | 21,373 | 6037 |
| 6 | 20 | 1678 | 40 | 10.9 | 4604 | 5213 | 25,282 | 3666 |
| 7 | 20 | 1831 | 64 | −5.0 | 1516 | 3604 | 33,516 | 1581 |
| 8 | 20 | 1727 | 83 | −16.3 | 2336 | 10,711 | 31,389 | 809 |
| 9 | 12 | 2779 | 34 | 11.1 | 5665 | 6690 | 20,998 | 6680 |
| 10 | 12 | 2883 | 42 | 8.7 | 4397 | 5349 | 25,224 | 4972 |
| 11 | 12 | 3020 | 64 | −6.5 | 1397 | 3942 | 33,296 | 1552 |
| 12 | 12 | 2861 | 82 | −20.8 | 2089 | 12,708 | 31,575 | 664 |
| 13 | 8 | 4087 | 27 | 8.6 | 5291 | 6101 | 20,142 | 7260 |
| 14 | 8 | 4186 | 37 | 6.7 | 4582 | 5690 | 23,002 | 5903 |
| 15 | 8 | 4576 | 64 | −7.3 | 1228 | 4263 | 33,979 | 1402 |
| 16 | 6 | 4197 | 84 | −17.3 | 1588 | 10,399 | 23,135 | 460 |

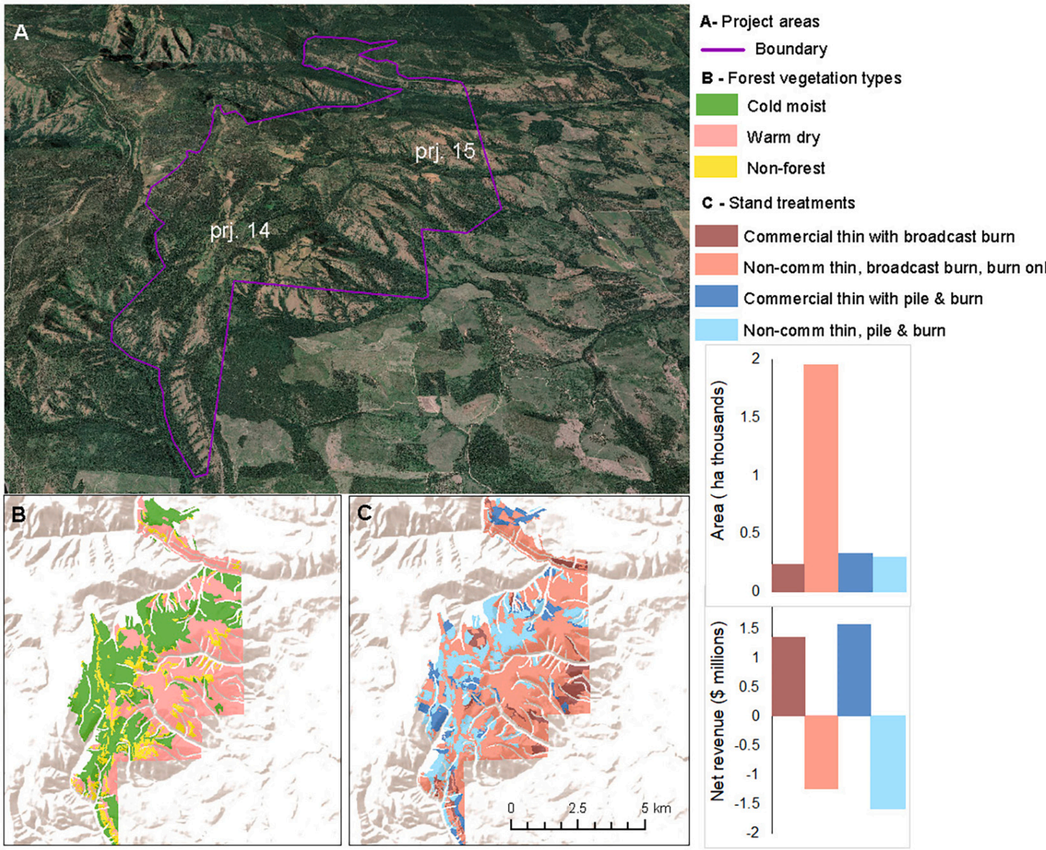


**Fig. 3.** Two example projects treating a total of 3235 ha with 42% dry forest from a scenario with a 1620 ha project area constraint and 25% minimum dry forest constraint (Scenario 6). A) Project areas overlaid on aerial photos across forest and non-forest grass-shrub vegetation, B) composition of forest vegetation types, and C) stand treatments including Commercial thin with broadcast burn (most often in dry, warm forests); Commercial thin with pile & burn (most often in cool, moist forests); Non-commercial thin, pile, & burn (usually in cool, moist forests); Non-commercial thin, broadcast burn (done in dry, warm forests) or Burn-only (done in grassland/shrub). Bar charts show total area treated and net revenue by treatment type.

demonstrate possible implementation of projects over the next 5 years. The two scenarios were chosen because both have a high percentage of dry forest, yet they differ in terms of the need for external investment. The scenario with small projects (Scenario 3) did not require any external investment while treating >50% dry forests, whereas larger projects with >75% dry forest (2700 ha, Scenario 12) required the largest amount of investment among the 16 scenarios to complete all of the selected projects.

Fig. 7 shows restoration treatment scheduling for the example scenarios explained above (Scenarios 3 and 12). The total area of commercial thinning activities was slightly higher for small projects (Scenario 3) with 681 ha treated per year, while larger projects (Scenario 12) treated 612 ha per year on average during the first 4 years. However, much larger differences were evident for non-commercial thinning, with smaller projects (Scenario 3) treating only 970 ha per year and larger projects (Scenario 12) treating 3087 ha per year. This is a direct result of treating more dry forest which is evident when project size is held constant and only the dry forest percentage is changed (Scenario 3 vs 4 in Table 3). The large amount of broadcast burn treatments in both scenarios is due to the high percentage of dry forest stands as well as significant area of grass-shrub stands burned within the projects. Scenarios 3 and 12 broadcast burned 4043 ha and 5228 ha of dry forest stands per year, corresponding to 69% and 84% of the total area to be treated with broadcast burn, respectively (the remainder = grass shrub).

## 4. Discussion

Expanding the footprint of broadcast burn in dry forests poses economic challenges that can potentially be mitigated by project designs that expand the diversity of ecological conditions to include more productive mixed conifer forests that generate revenue from commercial thinning. While this practice is not unknown to planners, quantification of the parameters, benefits and tradeoffs has heretofore not been shown, and to some extent may be especially important in diverse forest ecosystems like the Blue Mountains where steep gradients in productivity are widespread. The diversity in ecological conditions results from rapid changes in aspect, slope (Stine et al., 2014), and localized ash deposits from Mt. Mazama that create sharp transitions in soil productivity (Geist and Cochran, 1991), magnified by elevational gradients in moisture (Fig. 3). Our prior work on prioritizing restoration projects demonstrated steep tradeoffs between revenue and other management goals, including protecting the wildland urban interface, treating ecological departure, and improving stand resiliency (Belavenutti et al., 2021; Vogler et al., 2015). Additional studies are needed to streamline economic analyses performed in these studies as part of large-scale forest restoration programs (Butler and Schultz, 2019) given that economics will continue to be a barrier to increasing the pace and scale of restoration on western US national forests (Stine et al., 2014).

In terms of specific findings, increasing treatment area that targeted dry forests above 50% of the project area resulted in negative revenue for most of the scenarios (Fig. 5). On average, projects with more dry forest (>50%) had only 6% of the area treated with commercial thinning, whereas decreasing the dry forest component (<50%) increased

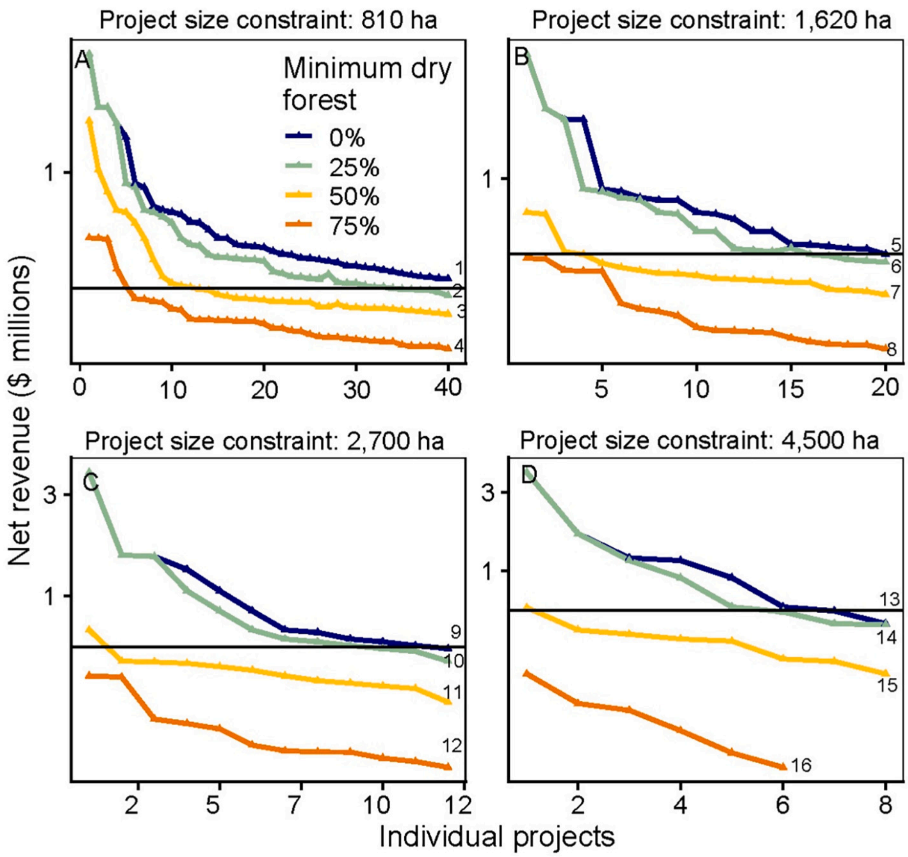


**Fig. 4.** Effect of dry forest percentage and project size on net revenue of individual project areas selected in each restoration scenario. Each panel represents a different project size constraint, while lines in each panel show different levels of dry forest. Numbers next to line graphs indicate the scenario identification number in Table 2.

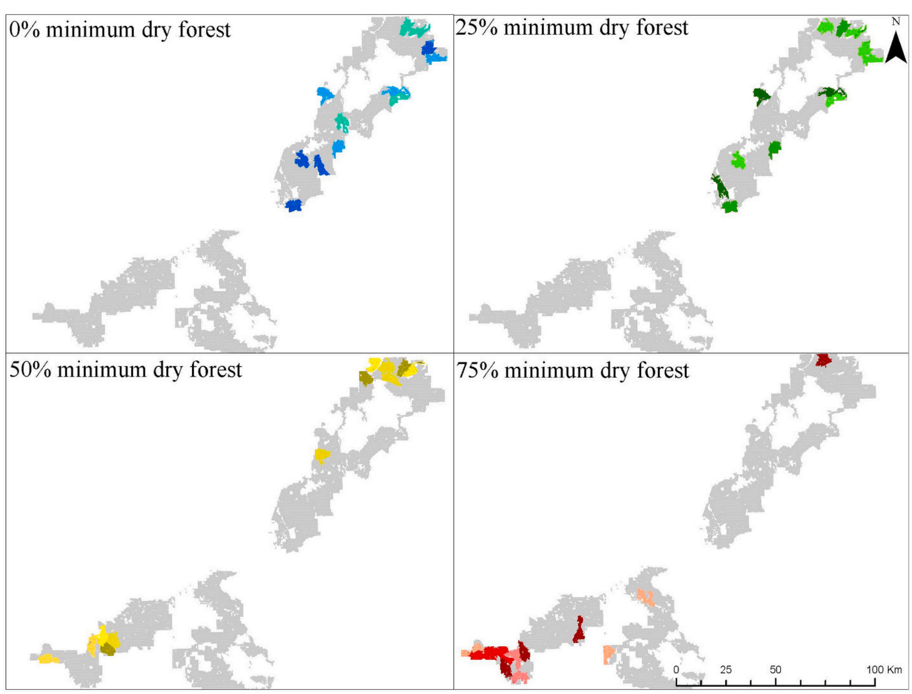


**Fig. 5.** Project area locations selected for scenarios with a 2700 ha project size constraint. Each panel represents results from scenarios where the dry forest percentage constraint varied.

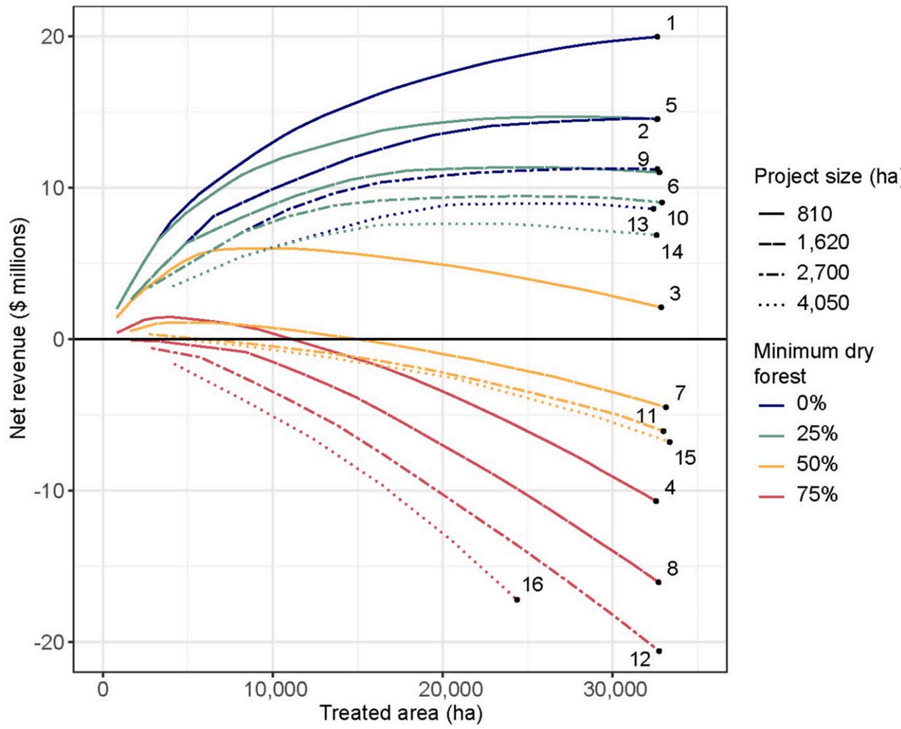


**Fig. 6.** Cumulative net revenue as more project areas are treated in each restoration scenario. Numbers next to line graphs indicate the scenario identification number in Table 2.

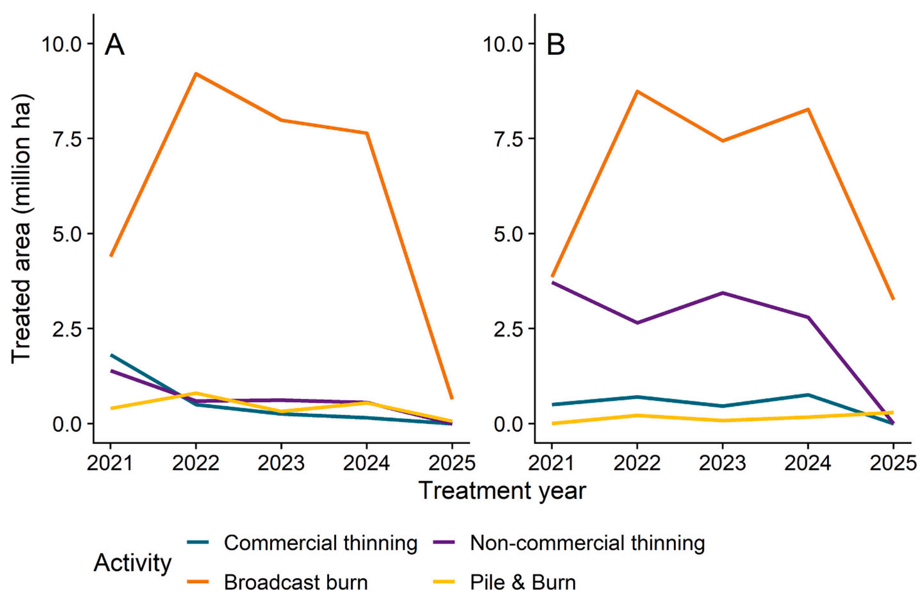


**Fig. 7.** Treatment activity schedule for two example scenarios showing the distribution across the 5-year planning horizon: A) Scenario 3 treated 40 projects of about 900 ha each with 50% minimum dry forest, and B) Scenario 12 treated 12 projects of about 2900 ha each with 75% minimum dry forest.

the area of commercial thinning to 17%. However, increasing the dry forest component (>50%) also resulted in 74% of the area treated with broadcast burning versus only 35% in areas with less dry forest (<50%) impacting the cost of restoration. Additionally, we observed that increasing project size resulted in a shift in the location of the optimal project, and a reduction in net revenue (Appendix A Fig. A2). However, we note that larger project areas bring about increased scale efficiency in terms of operational aspects of performing the treatments (Florec et al., 2020).

Although prior studies in the western US experimented with spatial prioritization for broadcast prescribed fire, our modeled scenarios integrated the full spectrum of treatments typically incorporated into restoration projects as part of the planning process (Belavenutti et al., 2021; Jain et al., 2012; Stephens et al., 2021). The suite of treatments is tailored to specific stand types as defined by potential vegetation type, surface fuel loadings, density, and species composition (Table 1). About 80% of the prescribed fire in the interior forests of the Pacific Northwest integrate broadcast burn as part of a suite of treatments to address a range of ecological conditions and restoration issues (Personal communication, A. Stinchfield, US Forest Service). Clearly, integrating a full range of treatments that are tightly coupled in sequence requires prioritizing the entire treatment package rather than a single treatment. For instance, several prior studies evaluated opportunities for broadcast prescribed fire as stand-alone treatments using spatial factors including wildfire hazard, vegetation and fuel types, historical fire regimes, presence of existing fuel treatments, wildland-urban interface development, and predicted broadcast prescribed fire behavior (Addington et al., 2020; Hmielowski et al., 2016). In other studies, a wide range of ecosystem services combined with fire behavior metrics were examined as part of prioritizing restoration projects (Hessburg et al., 2013; Kreitler et al., 2019; Schroder et al., 2016; Stephens et al., 2021). However, ecosystem services examined in these latter studies do not generate revenue that can subsidize, directly or indirectly, broadcast burn and other required investments to plan and implement restoration projects.

There are many decision support tools in forest planning that use a variety of methods to solve spatial optimization problems (Baskent and Keles, 2005). These include exact methods (Bellavenutte et al., 2020; Carvajal et al., 2013; Constantino et al., 2008; Dong et al., 2015; Goycoolea et al., 2009; McDill et al., 2002; Tóth et al., 2012) traditionally implemented with mixed integer linear programming methods. This approach requires significant processing time to find optimal solutions for stand aggregation problems and are generally too complex for implementation by field units. Heuristic methods can overcome some of these limitations (Bettinger and Boston, 2017). In the current study, our heuristic *Patchmax* (Appendix B) spatial module provided an efficient optimization process without the complexity of exact methods. To our knowledge the algorithm is the first application of network analysis to prioritize wholistic restoration projects and treatments within them. However, graph theory has been used in related work on treatment optimization, where fuel breaks were optimally located to impede the spread of fire (Finney, 2002; Gray and Dickson, 2016; Pais et al., 2021). Our algorithm obtained a typical solution in <5 s for over 50 thousand stands in the study area, which is about 10,000 times faster than other methods used for similar problems (Ager et al., 2016). The gain in efficiency was achieved by designing *Patchmax* to explore most but not every possible combination of stands to maximize the objective.

Multiple legislative and policy initiatives have set the stage for expanding the scale of restoration project planning and broadcast burning treatments within them on fire excluded forest landscapes (2021; USDA Forest Service, 2018). As the scale of projects grows larger, landscape planners will be increasingly challenged to design landscape restoration strategies where a wide range of localized reference conditions exist within a single project area, including the amount and pattern of patch scale heterogeneity in forest structure important for long-term resiliency (Hessburg et al., 2015; Stine et al., 2014). Likewise, maintaining long-term resiliency with the application of unplanned and planned fire treatments will also present challenges in terms of achieving desired patterns of fire severity among and within different fire regimes in larger planning areas. Layered on these general principles of landscape restoration is the economic reality that fire excluded landscapes on national forests will not be prioritized for implementing pyrosilvicultural treatments (North et al., 2012) if revenue cannot be generated from thinning activities. Landscape modeling approaches like that presented here, and other types of forest modeling systems (Cannon et al., 2020) have a potential role to help landscape planners leverage scenario planning science to examine alternative treatment scenarios and their efficacy and restore fire resiliency within fire excluded landscapes.

## 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.


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## Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2022.107558.

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