FINAL REPORT

For project task (#2)

5 January 2018

Report on the potential application of CFLRP monitoring tools for development of Forest Plan monitoring

In partial fulfillment of

USFS-CSU Agreement #12-CS-1

1021000-033 Mod. 6

Submitted to:

Arapaho & Roosevelt National Forests & Pawnee National Grassland

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Recommended citation:

Cannon, JB, KJ Barrett, BM Gannon, 2018. Report on the potential application of CFLRP monitoring tools for development of Forest Plan monitoring. Report to the Arapaho Roosevelt National Forests and Pawnee National Grassland. Colorado Forest Restoration Institute, Colorado State University, CFRI-1812

CONTENTS

1 REPORT SUMMARY

To aid in the development of monitoring strategies for the ARP forest plan, this report aims to (1) provide guidance on current ecological monitoring efforts conducted through the Front Range Collaborative Forest Landscape Restoration Program (CFLRP), (2) demonstrate application of these efforts to ARP forest plan monitoring, and (3) discuss advantages and limitations of current and potential monitoring efforts. This report focuses on monitoring the impact of restoration treatments on forest structure, composition, and spatial patterns; wildfire hazard and WUI risk; protection of soil and water resources; and enhancement of wildlife habitat. The analyses presented in this report are included to demonstrate potentially useful methods for conducting landscape-scale monitoring and to lay the groundwork for future discussions to further develop and adapt these strategies as appropriate for the ARP. The results presented are preliminary and not intended to inform any specific management decisions without further discussion and development in collaboration with ARP staff.

Plot-based monitoring of forest structure for the CFLRP using Common Stand Exam (CSE) data generally show that restoration treatments achieve basal area reductions of approximately 30% and density reductions near 50% with minor changes in overstory composition. Remote sensing methods suggest that CFLRP restoration treatments decrease canopy cover, and increase the size, complexity, and continuity of gaps. ARP management activities in the Red Feather generally follow these broad trends. However, field-based approaches may not be feasible forest plan monitoring, thus we review some recent remote sensing techniques that may be applicable. Recently developed remote sensing tools such as LandsatLinkr may be an ideal tool for tracking large changes in forest structure at the large spatial and temporal scales required for forest planning.

To demonstrate a potential approach for monitoring changes in wildfire and WUI risk, we used a USFS wildfire risk assessment framework to estimate changes in wildfire WUI risk from fuel reduction treatments in the Red Feather area. Combining data on wildfire probability with fire intensity potential information from FlamMap, and a remotely sensed WUI map, we found that fuel treatment effects in the Red Feather area vary due to starting forest conditions, fuel treatment types, and placement of treatments relatively to WUI. Metrics of WUI risk are sensitive to spatial definitions of the WUI, so it is important to clearly define metrics used in goals and objectives when monitoring wildfire risk reduction at a landscape scale. See text for complete details.

To demonstrate potential approach for monitoring forest management practices on reducing the potential for post-fire erosion, we used a linked-model approach coupling information on fire probability and intensity with models of erosion and sediment delivery. We found that fuel reduction treatments in the Red Feather area decrease post-fire erosion hazard in treated areas by 48-70% in the first year post-fire. In addition, we found that the hazard of sediment delivery to streams is concentrated in a few canyons, especially North Lone Pine Creek, as well as the high slopes of the Bald Mountains. Such information is potentially useful for both planning and prioritization of treatment in areas with steeper slopes or higher fire likelihood which may result in larger reductions on landscape-scale erosion risk.

Lastly, we outline the landscape-scale approach used by the Front Range CFLRP to monitor wildlife abundance and habitat. Components of this approach may be adopted and/or adapted for use in the ARP monitoring plan. We outline the filtering process used by the CFLRP to select 12 focal species/guild for monitoring based on species distributions, ecological function, conservation status, potential management impacts, and sampling logistics. We also include a summary description of the monitoring approach and protocols adopted by the CFLRP and currently being implemented by the Bird Conservancy of the Rockies to monitor avian communities.

2 INTRODUCTION AND APPROACH

The Challenge Cost-Share Agreement (12-CS-11021000-033) between the Arapaho & Roosevelt National Forests & Pawnee National Grassland (ARP) and the Colorado Forest Restoration Institute (CFRI) at Colorado State University includes a project (Modification 6) to explore the extent to which project-scale monitoring conducted by CFRI can be leveraged with other data to develop landscape-scale monitoring tools for the ARP. This report describes the outcomes of this project.

In compliance with the 2012 National Forest System Land Management Planning Rule, every National Forest is required to develop and implement a Forest Plan Monitoring strategy to assess trends and the effects of national forest management on key resources. The Arapaho-Roosevelt national Forest–Pawnee National Grass land (ARP) is currently developing monitoring protocols to assess the effectiveness of management activities toward achieving their Forest Plan's desired objectives. The current ARP Monitoring Plan ("monitoring plan") enumerates several goals and questions related to ecological processes to be monitored at landscape-scales. A few of the landscape-level goals outlined in the monitoring plan include:

- assuring a range of forest structural stages of community types (question 3),
- reducing the number of acres with high risk of wildfire (question 10),
- preserving and protecting water and soil resources (question 12),
- assessing the status of influential and dependent wildlife species (question 6),
- and assessing how management activities influence aquatic ecosystems (question 5).

The Colorado Front Range Collaborative Forest Landscape Restoration Project (CFLRP) seeks to implement fuel reduction and ecological restoration through forest management on U.S.D.A. Forest Service (USFS) lands including the ARP and the Pike & San Isabel National Forests. Within the Colorado Front Range, approximately 1.5 million acres of forests have been identified as in need of fuel reduction treatments and/or ecological restoration (Front Range Roundtable Fuels Treatment Partnership 2006). Similar to the goals of the ARP monitoring plan, this program emphasizes ecological monitoring of management impacts at landscape-scales.

Given the overlap in goals and geography with CFLRP monitoring, development of the ARP monitoring plan may be informed by monitoring methodologies and tools being used by the CFLRP. Such consideration can facilitate potential adoption or adaptation of analytical approaches useful for the ARP monitoring plan. The goals of this report are to

1. present an overview of landscape-scale monitoring currently utilized by the CFLRP,
2. present pilot analyses of ARP thinning treatments to demonstrate potential outputs produced by these monitoring strategies,
3. discuss applicability of CFLRP approaches to ARP monitoring
4. explore other potentially applicable monitoring approaches, and
5. create a foundation for development of a landscape-scale monitoring toolbox in cooperation with ARP staff.

Based on the monitoring priorities above, in this report, we address monitoring for management impacts on (1) forest structure, composition, and spatial patterns (Section 3), (2) wildfire hazard and WUI risk (Section 4), (3) protection of soil and water resources (Section 5), and (4) enhancement of wildlife habitat (Section 6). We conducted pilot analyses at the HUC-12 watershed scale, focusing on forested portions of several HUC-12 sub-basins in the Red Feather area (e.g., Elkhorn Creek and the North and South Fork Lone Pine Creek sub-watersheds, average extent of approx. 21,000 acres each) where treatment data from the Front Range CFLRP is readily available. This scale of analysis was chosen to be large enough to include multiple treatment areas, while small enough to feasibly conduct pilot analyses. Pilot analyses were demonstrated over a 5 year period (from 2010–2014) in order to match the current availability of Landfire data used in the fire behavior monitoring.

In the sections below, we outline an exploratory framework for landscape-scale monitoring of several key questions from the ARP monitoring plan. The analyses consist of the compilation of currently existing data from the ARP (e.g., CSE, and satellite imagery), the use of currently existing models of fire hazard and erosion potential (e.g., FlamMap, RUSLE), an exploratory assessment of CFLRP wildlife monitoring data, and potential approaches for aquatic ecosystem monitoring.

The analyses presented in this report are intended to demonstrate potentially useful methods for conducting landscape-scale monitoring at the ARP. The pilot analyses are intended to illustrate required data, methodologies, and potential outputs of various monitoring approaches. *The results in this report are not intended to inform any management decisions in their current state.* Rather, further discussion and development of these approaches with ARP staff will be required so that appropriate adjustments can be incorporated to best address particular management concerns of the ARP.

3 FOREST STRUCTURE, COMPOSITION, AND HETEROGENEITY

3.1 Demonstration of CFLRP approach

The current monitoring plan (see excerpt in Table 1) calls for "assuring representation of the full range of structural stages of community types" across the ARP (question 3), calling for forest management to "retain old-growth qualities" and restore "compositional, structural, and functional elements" of forests that will "perpetuate diversity". The plan suggests assessment of indicators such as forest composition, structure, and spatial heterogeneity.

The approach of the Front Range CFLRP to monitor management impacts on elements of forest structure emphasizes stand-scale measurements of changes in forest structure and composition as a results of restoration treatments (Cannon et al.; Addington et al. 2014; Cannon and Barrett 2016; Barrett et al. 2017). In addition, the CFLRP utilizes landscape-scale assessments of individual restoration treatments to determine how management actions alter forest structural patterns, particularly emphasizing the assessment of gaps, tree groups, and isolated scattered trees (Cannon et al. in prep; Dickinson 2014; Pelz and Dickinson 2014; Cannon and Barrett 2016). Here we present an overview of the methodologies used by the CFLRP to assess forest structure, composition, and spatial patterns, and we demonstrate application of these methods in the Red Feather area of the ARP.

3.1.1 CFLRP approach for forest structure and composition monitoring

Common Stand Exam (CSE) plots are standard inventory procedures implemented by the USFS before silvicultural management activities. Because surveys are regularly implemented prior to forest management, they provide an excellent opportunity to obtain pre-treatment monitoring data and a framework for plot-based monitoring. The CFLRP approach advocates re-measuring CSE plots to facilitate implementation and ecological monitoring. This approach provides valuable insight to changes in forest composition and structure resulting from management activities. When implementing CSE plots for forest compositional and structural monitoring, the CFLRP approach recommends stratifying an area by cover type, treatment type, and aspect, with at least three plots in each stratified area with accompanying control plots.

Table 1. Excerpt from ARP Draft Forest Plan Monitoring Questions related to changes in forest structure, composition, and spatial heterogeneity.

Monitoring Questions	Forest Plan Direction	Indicators
3. Has the ARP made progress toward assuring adequate representation of the full range of structural stages of community types across the Forests and Grassland?	Goals (excerpt): 3. In ponderosa pine and Douglas-fir forests, manage existing old growth and mature forests to retain and encourage old-growth qualities. 8. Provide a range of successional stages of community types across the Forests and Grassland landscapes that maintains ecosystem integrity. 34. Maintain and restore where necessary, the compositional, structural, and functional elements which will perpetuate diversity	Forest composition, structure, and spatial heterogeneity

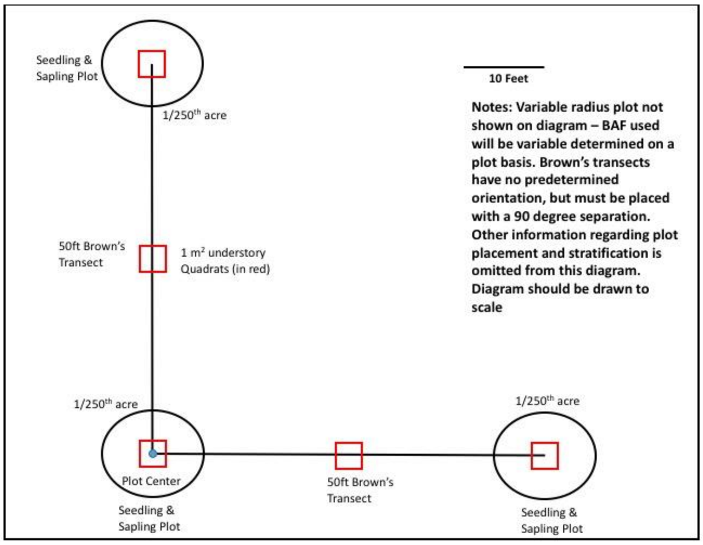


Figure 1. CSE plot design recommended for CFLRP monitoring. Note that analyses in this report only utilize at variable radius (BAF 10) plot centered over plot center

The CFLRP approach has suggested numerous modifications to traditional CSE plots (Figure 1), to help address the diverse monitoring questions intrinsic to Front Range forests (Barrett et al. 2017). Briefly, CSE plots include one overstory subplot, two Brown's transects for measurement of surface fuels, three regeneration subplots, and five understory vegetation subplots. Overstory subplots are variable radius (BAF 10) plots around used to tally trees > 5 inches diameter at breast height (DBH). For each tree, species, DBH, height, crown base height, live crown ratio, canopy position, and signs of animal damage are recorded. The two Brown's transects are standard, orthogonal 50-foot-long transects, intended to measure litter and duff depths; and 1-, 10-, 100-, and 1000-hour fuels at regularly spaced intervals. See Barrett et al. (2017) and Brown (1974) for detailed protocols. The three regeneration subplots are fixed area (0.004 acre, radius = 7.45 ft.) subplots located over each plot center, and at the end of each Brown's transect. All seedlings (< 4.5 feet tall) and saplings (< 5 inches DBH) are tallied by species. Finally, the five understory subplots are 1 m^2 (10.7 ft^2), and are used to calculate percent cover of functional groups (grass, forb, shrub, litter, rock, and bare ground). These plots are located at plot center, in the middle of each Brown's transect, and at the end of each Brown's transect.

Given repeated measurements (pre- and post-treatment) at CSE plots, analyses can summarize changes in forest structure, composition, fuels, regeneration, and coarse understory cover as a result of forest management activity. Specifically, analyses for the CFLRP focus on changes in forest structure and composition, and include summaries of changes in basal area, tree density, quadratic mean diameter, and the proportion of ponderosa pine relative to other conifers.

3.1.2 Pilot results from Red Feather

We analyze available CSE data from the Red Feather area (Figure 2) to illustrate how changes in forest structure and composition can be monitored using the CFLRP approach, with an emphasis on forest density, quadratic mean diameter, and relative proportions of ponderosa pine. CSE data was obtained for the Red Feather 1, Red Feather 2, Red Feather 4, and Magic

Table 2 Changes in forest structure and composition metrics at Magic Sky. Pre- and post-treatment means (sd) are presented. Change between pre- and post-treatment means (Δ), and p-value resulting from two sample *t*-tests for unequal variances are presented. *Welch-Satterthwaite t-tests were conducted to account for unequal variances.

Variable	Pre-treatment	Post-treatment	Δ	p
Basal area ($ft^2\ ac^{-1}$)*	64.3 (37.0)	47.3 (26.5)	-17.0	0.0177
Trees density (ac^{-1})*	306.7 (390.4)	126.8 (233.2)	-179.9	0.0134
Quadratic mean diameter (inches)	9.1 (4.5)	11.7 (4.7)	+2.6	0.0079
Ponderosa pine basal area ($ft^2\ ac^{-1}$)*	53.1 (33.9)	37.9 (24.0)	-15.2	0.0199
Douglas-fir basal area ($ft^2\ ac^{-1}$)	8.0 (11.1)	7.3 (9.3)	ns	0.7641
% Ponderosa by basal area	85.4 (20.5)	79.4 (30.2)	ns	0.2918

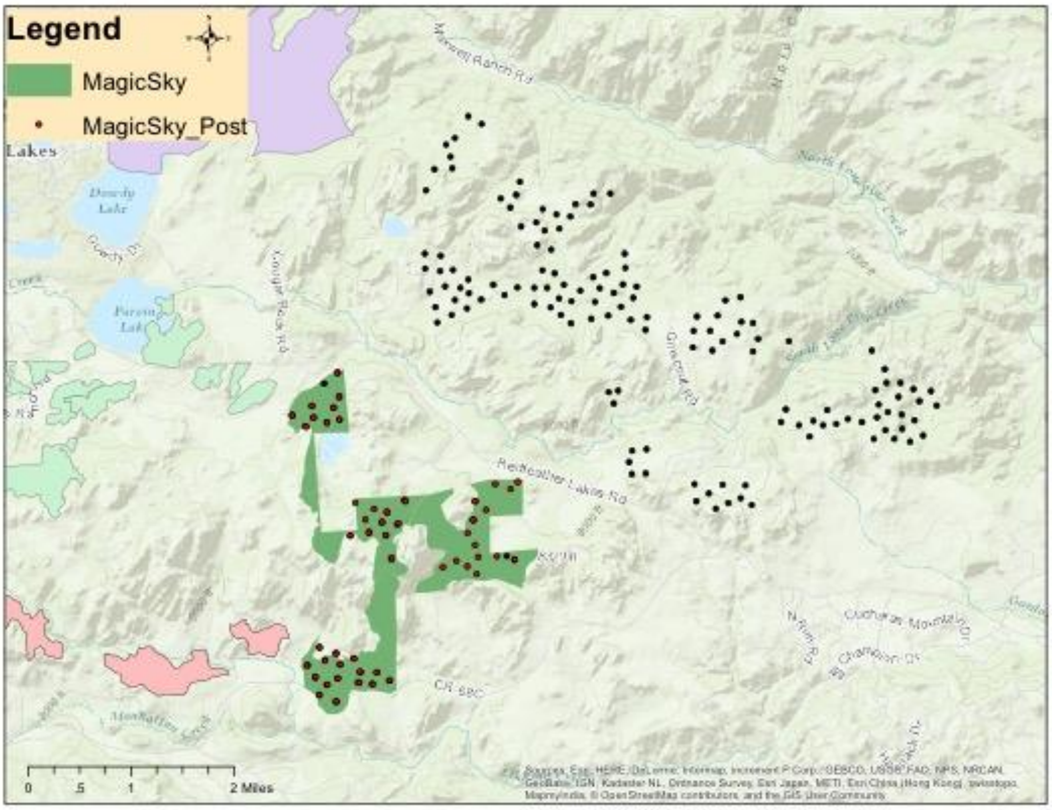


Figure 2. Map of Red Feather Area CSE Plots. Only pre- and post- treatment data was available for the Magic Sky project. Red points show 51 post-treatment plots (39 of which were available pre-treatment). Black points in the upper right show plots that fell outside of the treatment area

Sky projects within Red Feather area. Only pre-treatment data was available at Red Feather 1, Red Feather 2, and Red Feather 4, thus paired, pre- and post-treatment analyses could only be completed at in the Magic Sky treatment. Magic Sky had 217 CSE plots, however, only 90 could be used in analysis, as a large portion of points were outside of the treatment boundary. Of the 90 usable plots, 39 were pre-treatment, and 51 were post-treatment. The remaining 127 plots were outside the treatment area (Figure 2). Changes in forest structure and composition

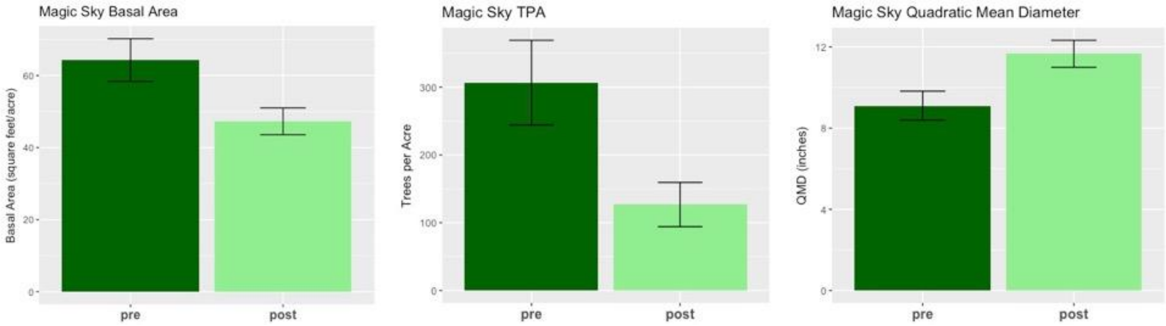


Figure 3. Magic Sky forest structure summaries. Basal area (left), tree density (middle) and quadratic mean diameter (right) pre- and post-treatment. Figures show mean values and standard errors.

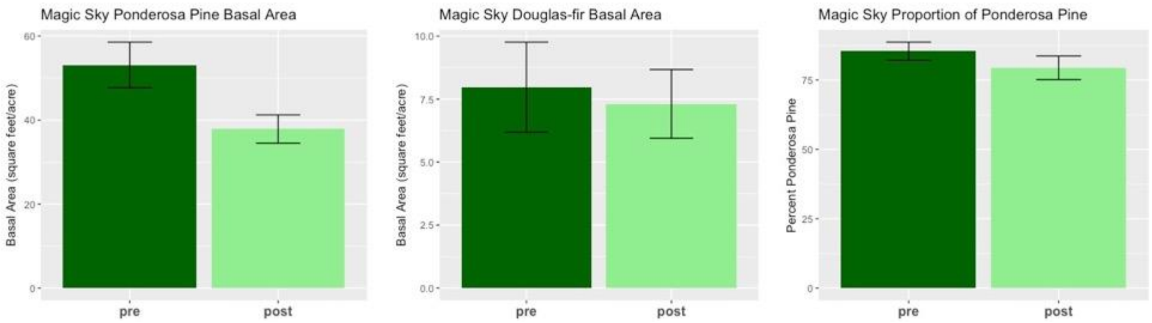


Figure 4. Magic Sky forest composition summaries. Ponderosa pine basal area (left), Douglas-fir basal area (middle), and proportion of ponderosa pine relative to other conifers (right) pre- and post-treatment. Figures show mean values and standard errors.

metrics among usable plots were tested using two sample *t*-tests comparing pre- and post-treatment plots.

Changes in forest structure were significantly different resulting from forest management (Table 2, Figure 3). Basal area decreased by 17 ft^2 ac^{-1}, tree density acre decreased by 179.9 trees ac^{-1}, and quadratic mean diameter increased 2.6 in. Conversely, for forest composition metrics, only ponderosa pine basal area was significantly lower after forest management (15.2 ft^2 ac^{-1} decrease). Although Douglas-fir basal area decreased 0.7 ft^2 ac^{-1}, and the percent of ponderosa pine by basal area increased 6%, none of these measures were significantly different between pre- and post-treatment measurements Table 2, Figure 4).

3.1.3 CFLRP approach for spatial heterogeneity monitoring

A primary goal of the CFLRP is for restoration treatments to "establish a complex mosaic of forest density, size, and age at stand and landscape scales," and the program has adopted a remote sensing approach to monitor how restoration treatments alter forest spatial structure. Remote sensing techniques are used to classify satellite or aerial imagery of restoration treatments into GIS layers classified as canopy and openings (protocol detailed in Cannon et al., forthcoming; Pelz and Dickinson 2014).

Briefly, cloud-free, snow-free, leaf-on, satellite imagery temporally flanking the dates of restoration treatments are acquired from three sources including WorldView-02 (WV02), GeoEye-01 (GE01), and/or Quickbird-02 (QB02) satellites with a spatial resolution of approximately 3 m and spectral resolutions ranging from 4- to 8-bands (Figure 5A). Satellite imagery is classified using a two-step approach beginning with supervised classification to classify canopy, openings, and shadows; shadows are subsequently classified into canopy and

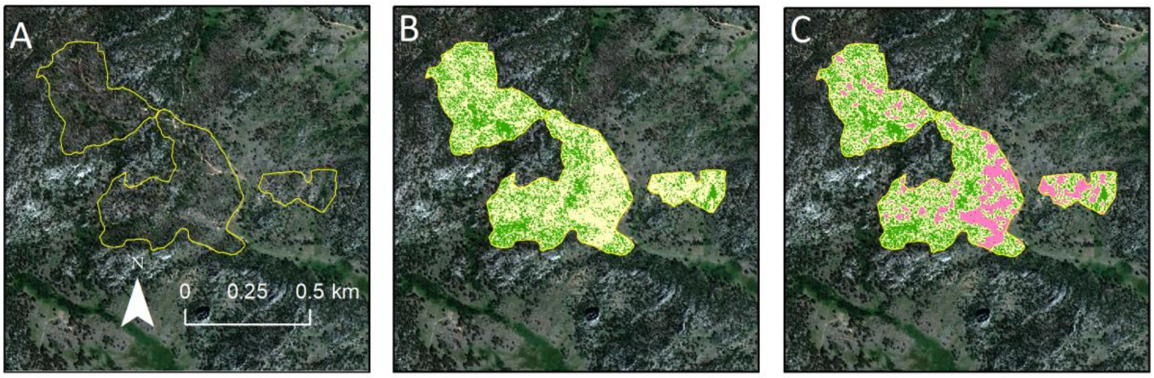


Figure 5. (A) Pre-treatment satellite imagery of Magic Sky area within the Arapahoe Roosevelt National Forest. (B) Classified imagery indicating canopy (green) and openings (yellow). (C) Demonstration of gap delineation (magenta) overlaid onto classified imagery indicating portions of imagery with <10% canopy cover over a 0.05 ha area.

Table 3. Treatment units analyzed within the Red Feather area. Thinning treatments were completed between 2010 and 2015.

Treatment Unit	Management activity	Area (ac)
Red Feather 1 FRP TU:10C	Pre-commercial Thin	121
Red Feather 1 FRP TU:18B	Pre-commercial Thin	111
Red Feather 1 FRP TU:18C	Pre-commercial Thin	36.9
Red Feather 1 FRP TU:19S	Pre-commercial Thin	72.4
Red Feather 1 FRP TU:17A	Pre-commercial Thin	64.3
Red Feather 1 FRP TU:17B	Pre-commercial Thin	8.50
Red Feather 1 FRP TU:19T	Pre-commercial Thin	12.0
Red Feather 1 FRP TU:25B	Pre-commercial Thin	8.89
Swamp Creek Trail	Thinning for Hazardous Fuels Reduction	18.9
Dowdy Lake Recreation Areas	Thinning for Hazardous Fuels Reduction	18.6
Pingree Hill FRP TU:5	Thinning for Hazardous Fuels Reduction	99.8
Pingree Hill FRP TU: 9A	Thinning for Hazardous Fuels Reduction	91.0
Dowdy Lake Campground	Thinning for Hazardous Fuels Reduction	69.4
	Total	733

openings using gray-level thresholding of NDVI values (Cannon et al., forthcoming; Lillesand et al. 2015). Classifications are trained by an analyst via stratification of approximately 100 training regions across areas identified as canopy, openings and shadows; and imagery is classified using a maximum likelihood classification in ArcMap 10 (Figure 5B). Following initial classification, areas reclassified as shadow are classified into canopy or openings using an image-specific NDVI threshold (Lillesand et al. 2015).

Each classified image is processed to estimate spatial metrics relevant to fine-scale spatial structure including canopy cover and openings. In addition, ‘large gaps’ are delineated in each classified image a modification of the PatchMorph algorithm (Girvetz and Greco 2007). Here, we define gaps as contiguous regions with < 5% canopy cover over an area of 0.045 ha (i.e., 12 m radius)—a neighborhood size relevant for abundance and growth of regenerating seedlings (Boyden et al. 2012). Gaps delineated for portions of the Magic Sky treatment area shown in Figure 5C. Once gaps are delineated, gap metrics including gap density, gap size distributions, shape index, and aggregation metrics such as nearest neighbor distances (McGarigal et al. 2012) are quantified using the `SDMTools` (VanDerWal et al. 2014) package in R. Last, metrics of shape and arrangement of gaps such as the gap decay coefficient

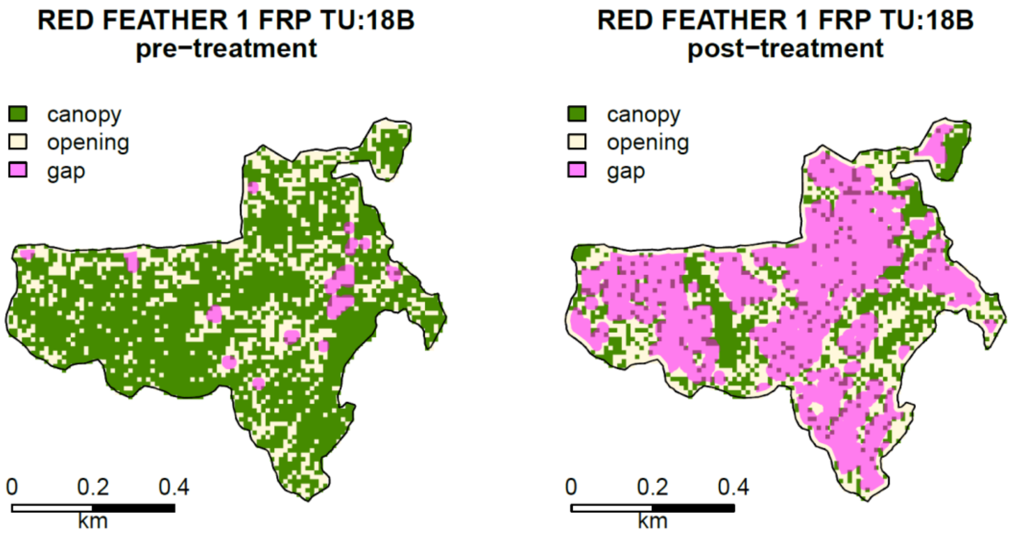


Figure 6. Example illustrating results of supervised classification and gap delineation. Figure illustrates canopy and gap cover before (left panel) and after (right panel) thinning treatments in one 111 acre treatment unit in the Red Feather area.

Table 4. Changes in spatial patterns resulting from 2010–2014 thinning treatments listed in Table 3. Pre- and Post-treatment means (s.d.) are presented. Change between pre- and post-treatment means (Δ), and *p*-value resulting from paired *t*-test comparing pre- and post-treatment means for each of the 13 treatment areas listed in Table 3.

Variable	Pre-treatment	Post-treatment	Δ	p
Canopy cover (%)	54.0 (14.9)	28.5 (5.24)	-25.5	0.0003
Gap cover (%)	26.0 (20.4)	54.0 (15.0)	+28.0	< 0.0001
Gap density (ha^{-1})	0.855 (0.452)	0.713 (0.373)	ns	0.2181
Median gap size (ha)	0.131 (0.102)	0.288 (0.531)	ns	0.3464
Gap size CV (unitless)	1.26 (0.692)	2.05 (0.787)	+0.791	< 0.0001
Median gap shape index (unitless)	0.986 (0.0824)	1.13 (0.258)	ns	0.1108
Nearest neighbor index (m)	27.2 (33.2)	8.00 (3.44)	ns	0.0648
Gap decay coefficient (unitless)	0.0568 (0.017)	0.0393 (0.0116)	-0.0175	0.0008

(modified from Collins et al. 2017) are calculated to evaluate changes in spatial patterns of gaps due to thinning and restoration treatments.

3.1.4 Pilot analyses of spatial heterogeneity metrics in the Red Feather area

Using the methods above, we illustrate how changes in forest spatial heterogeneity may be monitored with emphasis on changes in canopy cover and creation and maintenance of large gaps. Fuel reduction and restoration treatments completed in the Red Feather area were identified using the Hazardous Fuel Reduction Treatments database (US Forest Service Natural Resource Management 2017) from the U.S. Forest Service Activity Tracking System (FACTS). A summary of the thinning treatments included can be found in Table 3. Treatment boundaries for all thinning treatments completed during the 5-year period (2010–2015) were extracted, and satellite imagery was acquired, classified, and analyzed as described above (Figure 6). Thinning treatments completed in the Red Feather area during this period total approximately 730 acres. Statistical changes of spatial pattern metrics were tested using a paired *t*-test comparing pre- and post-treatment metrics in the 13 treatment units identified in the Red Feather area (Table 3). Imagery was not available for a single treatment area.

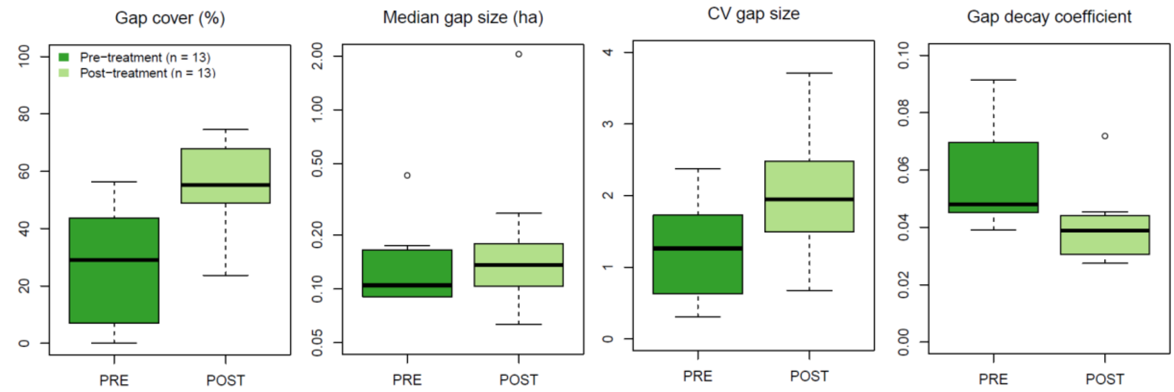


Figure 7. Changes in forest spatial patterns of fuel reduction/thinning treatments in the Red Feather area completed between 2010 and 2014. Note log scale on *y*-axis for median gap size.

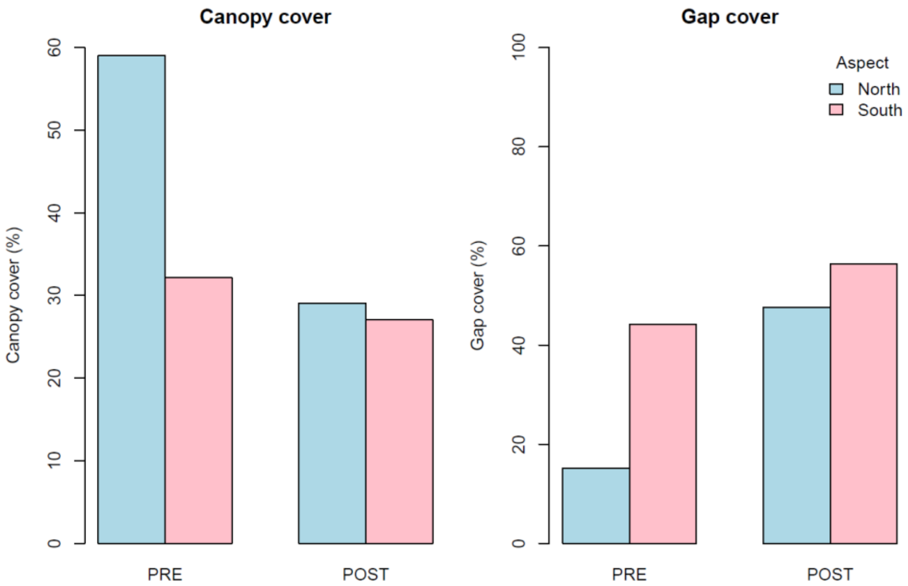


Figure 8. Comparison of pre- and post-treatment canopy cover and gap cover in Red Feather between north- and south-facing slopes.

Analyses of thinning treatments in the Red Feather area indicate changes in multiple aspects of canopy cover and gap spatial metrics. Notably, across the 13 treatment units examined, management activities decreased canopy cover from 54% to 29.5%, and more than doubled gap cover from 26.0% to 54.0% (Table 4). In addition, several changes in gap spatial pattern resulted from thinning treatments. Median gap size increased from 0.13 ha to 0.29 ha, although the change was not significant due to high variability in median gap size (Table 4; Figure 7). In addition, the coefficient of variation of gap size increased approximately 63% from 1.26 to 2.05 (Table 4; Figure 7) indicating an increase in gap size variability. Lastly, gap decay coefficient decreased from 0.0568 to 0.0393 (Table 4; Figure 7). This metric captures the size distribution of gaps (see Collins et al. 2017) and indicates that a greater proportion of gap area is concentrated into gap interiors (i.e., those areas distant from gap edges). Thus, gaps following thinning treatments can be characterized as larger and more continuous relative to the pre-treatment conditions.

Desired conditions of the Front Range CFLRP specify that forest structure and spatial patterns on ponderosa pine dominated forests on dry topographies (e.g., ridge or south-facing slopes) should differ from those on more mesic slopes (e.g., valleys, draws, north-facing slopes) in order to mimic natural drivers of heterogeneity (Dickinson and SHSFRR 2014). Specifically, desired conditions of the CFLRP suggest that gaps and openings should be larger and more frequent on dry slopes wile smaller and less frequent on mesic slopes so that heterogeneity at larger scales due to processes driven by topography can be maintained (Dickinson and SHSFRR 2014). It should be noted, however, that preliminary analyses of historical reconstruction data of the Front Range indicates that variability among aspects may be smaller than original expected (M. Battaglia, *unpublished data*). Here, we present summary data illustrating changes in canopy cover and gap cover before and after thinning treatments on north versus south slopes in the Red Feather area. Using a 30-m digital elevation model, north and south slopes were identified as any region with an aspect of 0 ± 45^{o} and 180 ± 45^{o}, respectively. Data on pre- and post-treatment canopy cover and gap cover was summarized within these regions for all treatment units indicated in Table 3.

As shown in Figure 8, before thinning treatments, canopy cover was twice as high on north-facing slopes (59%) relative to south-facing slopes (29%); however after thinning treatments north- and south-facing slopes had relatively similar levels of canopy cover (29% and 27% respectively). In a similar pattern, gap cover varied more between north- and south-facing slopes before thinning treatments (15% vs. 44%, respectively) compared to after thinning treatments (48% vs. 56%; Figure 8). Thus, variability in canopy cover and gap cover among topographic gradients was decreased by thinning treatments. Such analyses that compare changes in treatment outcomes across topographic gradients can inform how forest management activities at stand-scales may affect landscape-heterogeneity. However, careful consideration should be given to the outcomes expected and desired variability across these environmental gradients.

3.2 Application of CFLRP analyses

Application of CFLRP monitoring protocols for monitoring changes in forest structure, composition, and spatial patterns for landscape-scale monitoring presents synergies and challenges for application to ARP landscape-scale monitoring. Below we outline advantages and disadvantages of the CFLRP monitoring approaches and suggest alterations or alternatives to these approaches for ARP monitoring.

Common Stand Exam (CSE) data is collected regularly on the Forest prior to restoration treatments in order to understand forest structure for developing management prescriptions. For CFLRP monitoring these same protocols are also applied following restoration treatments to understand the extent to which implementation of the prescription achieved the desired goals in the short-term. An advantage of using CSE plots for ARP monitoring is that protocols and structures are already in place to allow CSE protocols to be collected by ARP directly or through subcontractors. However, the CSE approach also presents several challenges to consider for adoption to landscape-scale monitoring.

1. Data collection from CSE plots are typically implemented only in areas where treatment planning is underway, thus the current approach is not appropriate to capture change occurring in portions of the forest that are not under consideration for active management. In such areas, natural disturbances from fire, insect outbreaks, wind throw, and

demographic processes can alter forest structure in composition in ways that will not be captured by CSE plots alone.

2. Currently, post-treatment data from CSE plots are collected only for CFLRP-related projects (K. Zimlinghaus, *personal communication*). Due to changes in funding and/or contractors within some CFLRP projects, in many cases thinning and restoration treatments on the ARP do not have paired data (i.e., pre- or post-treatment data is missing), making consistent assessment of changes in forest composition difficult.
3. In a CFLRP monitoring report, Addington et al. (2014) noted that variable radius plots collected for project planning purposes are less useful for monitoring applications because different basal area factor prisms are used. Such inconsistencies in protocols can create challenges for analyses and inference. Thus, recent CFLRP monitoring efforts adopt consistent protocols for measuring tree overstory.
4. CSE plots are typically implemented immediately following forest management activities, thus their value for ecological monitoring is limited. Implementation of CSE plots at longer post-treatment intervals (e.g., 3, 5, or 10 years) could provide long-term insights on treatment ecological effectiveness, longevity, and their effects on various metrics such as fuels, regeneration, composition, and structure over time scales relevant for forest planning.

Spatial heterogeneity analyses currently implemented by the CFLRP for treatment monitoring offer an approach to monitoring changes in forest spatial patterns for the ARP. To the extent that they offer meaningful metrics related to Forest Plan monitoring, these methods can be readily adopted by the ARP to supply information on how specific management actions alter spatial heterogeneity in small landscapes (e.g., HUC-12). Commercially available satellite imagery is freely available for federal researchers and their collaborators through Digital Globe (http://digitalglobe.com). In addition, use of satellite imagery greatly increases the spatial and temporal extents over which treatment impacts on spatial heterogeneity can be evaluated relative to plot-based metrics developed to monitor forest heterogeneity (e.g., Briggs et al. 2017).

Two main challenges are associated with direct adoption of the spatial heterogeneity analyses of the CFLRP for ARP monitoring. First, processing, training, and analyzing satellite imagery requires advanced applications of GIS and remote sensing. CFRI is currently developing a spatial heterogeneity toolbox compatible with ArcGIS to increase efficiency, reduce costs, and alleviate barriers for resource managers interested in understanding changes in spatial patterns resulting from management actions. Second, while the spatial heterogeneity analyses offer inference of spatial patterns over larger temporal and spatial extents relative to plot-based metrics, such analyses remain challenging for monitoring at the scale of large landscapes such as the entire ARP. Compilation of full-coverage satellite imagery across an area as large of the ARP for multiple time points requires a high degree of manual imagery compilation, which is challenging due to the inconsistencies in seasonality, snow, and cloud coverage, which can obscure satellite imagery. To date, the Front Range CFLRP has avoided these difficulties by restricting analyses to smaller scales such as the stand-level analyses demonstrated above. Thus, spatial analysis at the scale of one-three HUC-12 watersheds (10,000-50,000 acres) may be feasibly conducted. In the next section, we outline two alternative approaches using remotely collected data (Landsat and LIDAR) which may provide relevant metrics applicable to landscape-scale Forest Plan monitoring.

3.3 Alternative monitoring approaches

3.3.1 Plot-based monitoring approaches

Ground-based plots will be required to evaluate many detailed aspects of forest structure and composition, (e.g., tree size distribution, fuel loadings, shrub and herbaceous abundance diversity, wildlife use, etc.). Current CSE data collected for the CFLRP includes only measurements of overstory trees and in some cases includes loading of woody surface fuels. However, CSE protocols have been developed for a number of additional aspects of forest composition (USDA Forest Service 2015). Relevant protocols can be amended to those currently collected by the CFLRP to provide complementary information for forest plan monitoring. In addition, ground-based data can be used to validate and calibrate remotely measured techniques using Landsat and/or LIDAR (see section 3.3.2 for further discussion). Techniques such as LIDAR are best calibrated using data from fixed-radius plots rather than variable-radius plots (Deo et al. 2016), which are the main form of stand inventories currently collected to monitor CFLRP projects.

In a report prepared for the Kaibab National Forest, Ray et al. (2013) propose a ‘rapid-plot’ design to provide information on variables such as diameter distributions of trees and snags, surveys of understory vegetation, fuels, and surveys for encroachment and non-native invasive species. Decisions on which response variables to measure in ground plots will be most applicable to the ARP Plan will require specification of desired conditions of various metrics so that efficient sampling protocols can be developed. A second important consideration for deployment of a ground-based sampling strategy is the spatial distribution of plots. The number of plots needed for monitoring will be determined by the desired frequency of sampling, the resources needed for sampling, and statistical considerations to detect changes in response variables of particular magnitudes. Ray et al. (2013) outline an approach for placing ground sampling plots across a large area such as an entire National Forest using data on vegetation cover types available from the Landfire Project (www.landfire.gov). Following Ray et al. (2013), ground plots can be randomly stratified across relevant vegetation types, and transformations such as a cube-root transformation of cover type area can be used to more efficiently place sample plots across frequent and infrequent vegetation types. Such transformations increase efficiencies by decreasing the sampling effort in dominant forest cover types, and increasing sampling effort in uncommon cover types. Table 5 illustrates how this stratification approach can be used in the ARP. Figure 9 shows Landfire existing vegetation types for Red Feather for the five dominant cover types. Table 5 shows estimated areas for each cover type and suggests how sampling effort may be distributed across cover types for an assumed 200 monitoring plots.

For the Front Range CFLRP, the majority of ecological monitoring is completed through plot-based sampling (Young et al. 2013; Addington et al. 2014). More recently, these methods have been complemented with analysis of aerial and satellite imagery (Cannon et al., forthcoming; Cannon and Barrett 2016; Dickinson et al. 2016) to increase the scale at which inferences of restoration effects on forest spatial heterogeneity can be made. Traditional sampling through

Table 5. Major existing vegetation types in Red Feather demonstrating example distribution of sampling points using a cubic-root stratification of sampling points. See Figure C for example of treatment placement by cover type in Red Feather using stratified sampling with cube-root transformation of area. Note that estimated plots in each vegetation cover type are for example only based on an arbitrary total sampling effort of 200 plots.

Vegetation cover type	**% Cover**	**Est. area (ha)**	**Cube root area (ha)**	**Sampling effort (%)**	**Est. plots (total n = 200)**
Interior ponderosa pine	28.1%	7,271	19.37	24.7%	49
Lodgepole pine	21.3%	5,508	17.66	22.5%	45
Interior Douglas-fir	20.8%	5,372	17.51	22.3%	45
Wyoming big sagebrush	6.8%	1,759	12.07	15.4%	31
Aspen	6.5%	1,686	11.90	15.2%	30
Total	83.6%	21,596	78.52	100.0%	200

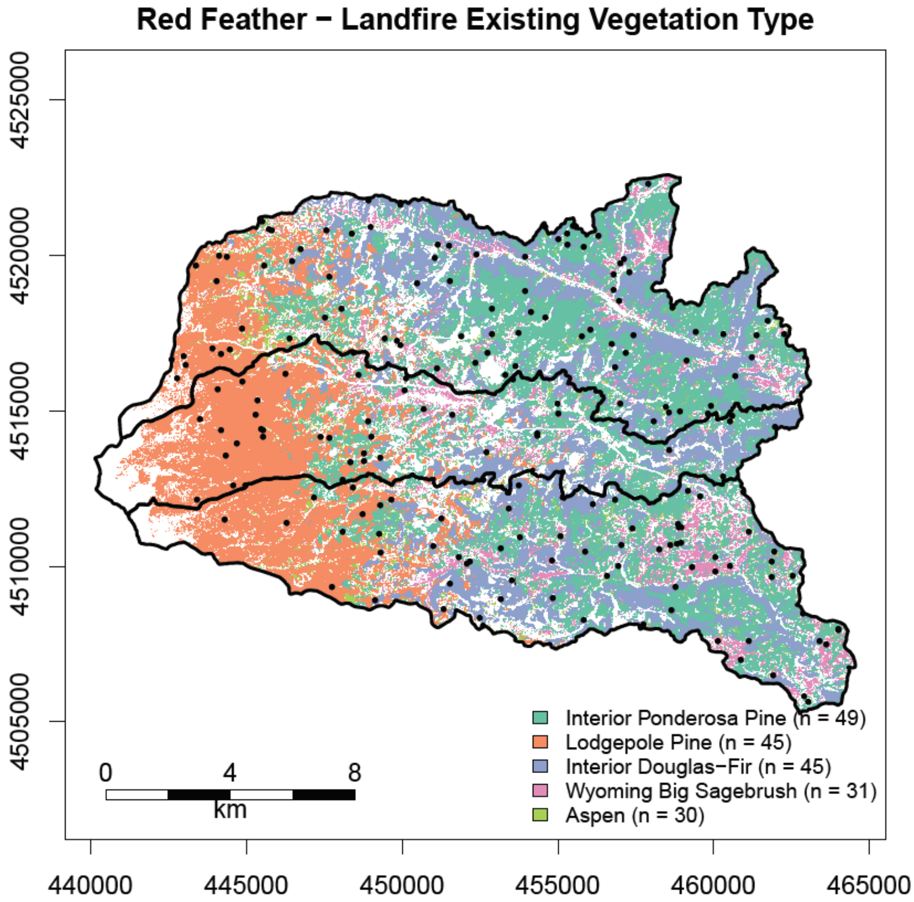


Figure 9. Major existing vegetation types in Red Feather demonstrating example distribution of sampling points using a cubic-root stratification of sampling points. See Table 5 for estimations of cover and sampling calculations.

plot-based approaches are necessary for many aspects of forest management planning, and they also have advantages for measuring changes in tree-diameter distributions, forest composition, and fine-scale changes in fuels, soils, understory composition, nutrient dynamics, and wildlife use. However, to best address monitoring questions at the landscape scale, approaches with larger spatial extents may be more appropriate for feasibly monitoring the status and trends of forest structure over extensive areas such as the ARP. Here, we outline potential applications of remote sensing techniques for landscape-scale monitoring of forest structure and composition across the ARP. Currently the CFLRP is engaged only in plot- and stand-scale analyses and few larger scale analyses have been conducted to assess changes in forest structure and composition from CFLRP treatments, although current efforts compiling treatment activities across large extents (e.g., Caggiano 2017) may lead to such considerations.

3.3.2 Remote-sensing based approaches (satellite and LIDAR)

In a report prepared for the Kaibab National forest, Dickson et al. (2011) explore potential application of Landsat TM for monitoring changes in forest structure which may be most directly applicable for use for ARP forest monitoring. Briefly, this study explored using Landsat TM imagery to predict forest structural metrics across the entire Kaibab National Forest based on training and validation data estimated from approximately 600 FIA plots. Available data from FIA plots were modeled in the Forest Vegetation Simulator (FVS) to estimate elements of forest structure to dates congruent with imagery acquisition dates. Dickson et al. (2011) found remotely derived approaches modeled stand density index, basal area, and canopy cover with over 70% of variance explained. All models of stand height explained > 80% of variance, and quadratic mean diameter was the least well-predicted with at most 60% of variance explained by remotely derived models (Dickson et al. 2011). Importantly, this report illustrates how multi-spectral and multi-temporal satellite images can produce reliable estimates of forest structure over time at very large scales. Given the large spatial and temporal extents that can be explored using remote sensing techniques, and the relatively high accuracy at large spatial scales, such approaches may be ideal for monitoring broad trends in forest structure at large scales for the ARP. Application of this and other approaches can be explored in future endeavors.

Recently, code libraries developed for R statistical software have been developed to allow rapid analysis of satellite imagery (through Landsat earth observation program) over large spatial extents and large temporal domains relevant to monitoring status and trends in forest structure for forest planning (e.g., between 1-40 years). A recent study by Vogeler (in review) outlines a framework combining two such code libraries to analyze long-term changes in forest canopy cover across the entire state of Minnesota. The LandsatLinkr package in R (Braaten et al. 2017) was used to process, mask, harmonize, and composite Landsat imagery from 1973–2015. Next, the LandTrendr package (Kennedy et al. 2010) was used to minimize intra-annual noise to produce linearized trends for each 30-m pixel in the state of Minnesota to better represent forest dynamics and aid in the identification forest growth, decline, and disturbance events. Once all imagery was stacked and processed, estimates of canopy cover across the entire state were generated using training data created using publicly available aerial imagery. Vogeler et al. (in review) used this technique to produce maps of forest cover over a 43-year period with 88% accuracy. These maps were used to identify major changes in forest cover across the entire state from 1973 to 2015 (Figure 10). Using this approach, data layers estimating changes in canopy cover or other forest structural metrics (e.g., basal area, QMD, SDI, etc.) could be generated for the extent of the ARP at the large spatial (10,000 to 1,000,000 acres) and temporal (1-40 years) domains relevant for forest planning. In addition, landscape-scale estimates of forest structure can useful for modeling management impacts on other aspects of forest monitoring such as potential wildlife habitat (see approach in Stevens et al. 2016).

Light detection and ranging (LIDAR) has been useful for estimating forest characteristics such as basal area, biomass, successional stage, etc. and may be a useful tool for monitoring status and trends of forest structure on the ARP. Lidar data is publicly available for large portions of

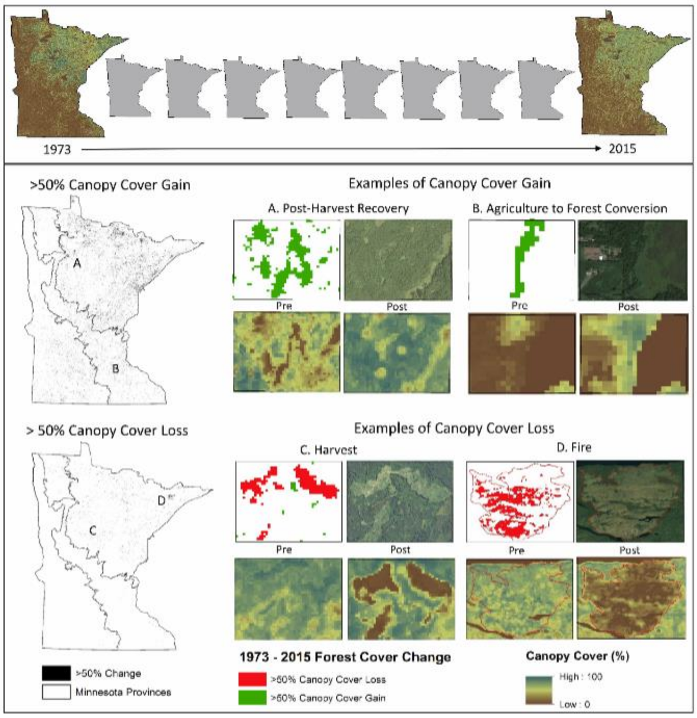


Figure 10. Demonstration of the use of LandsatLinkr and LandTrendr algorithms used to predict changes in canopy cover across Minnesota from 1973–2015. Changes in canopy cover over type can be used to identify forest growth (A, B), decline, or canopy loss due to disturbances (C, D). From Vogeler et al. (in review).

Larimer and Boulder counties through the Colorado Geological Survey (Figure 11) providing a detailed snapshot of forest structure (Figure 12), which can be analyzed to provide information on characteristics of forest structure for forest monitoring at fine spatial scales.

One major reason for monitoring status and trends of forest structure is to better understand the distribution of successional stages across managed lands. Understanding the representation of forest successional stages (e.g., stand initiation, stem exclusion, old growth stages, etc.; O'Hara et al 1996), is an important component of understanding landscape dynamics, silvicultural trajectories, and wildlife habitat availability. Lidar data has been shown to be a great tool for estimating the distribution of successional stages across structurally diverse forests over large extents (e.g., ~30,000 ha). Briefly, LIDAR data can be processed to extract multiple metrics relating to the vertical and horizontal distribution of vegetation (e.g., maximum canopy height, mean canopy height, canopy cover, etc.) which can be used to predict forest structural metrics such as basal area, volume, QMD, SDI, among others (Falkowski et al. 2010) as well as structural stages across large extents. Falkowski et al. (2009) demonstrate this approach for a mixed conifer forest in northern Idaho. This study illustrates how LIDAR data can be combined with a relatively small number of forest inventory plots (i.e., ~80) in order to characterize forest structural stages across the landscape. This study demonstrated that forest structural stages can be estimated with high accuracy (90–95%; Figure 13) across very large scales. The ARP forest monitoring plan explicitly calls for monitoring the status and trends of forest successional stages, and tools such as LIDAR could play an important role in monitoring changes in forest

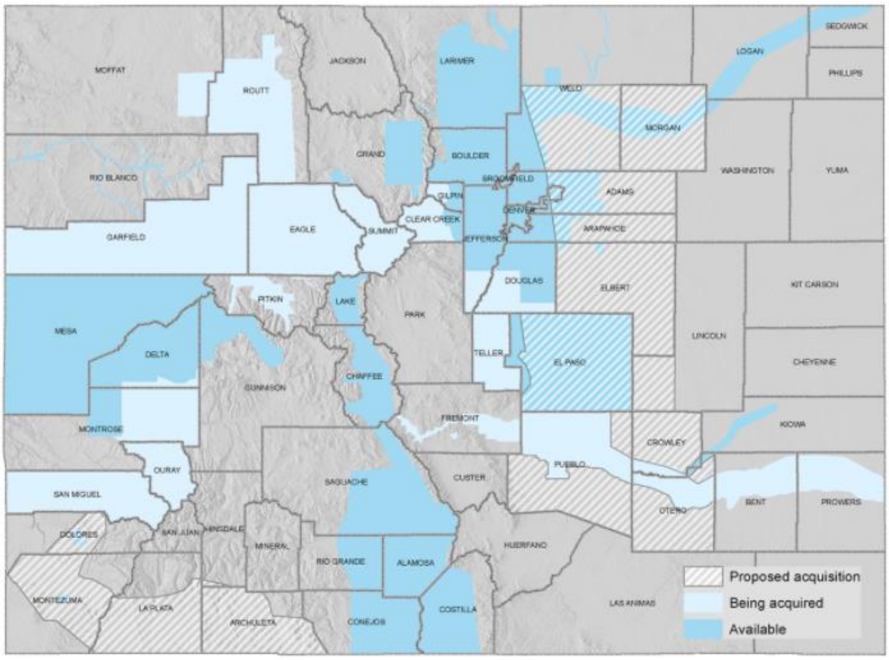


Figure 11. Feb 2017 Lidar acquisition map for the state of Colorado. Colorado Geological Survey, available online: http://coloradogeologicalsruvey.org.

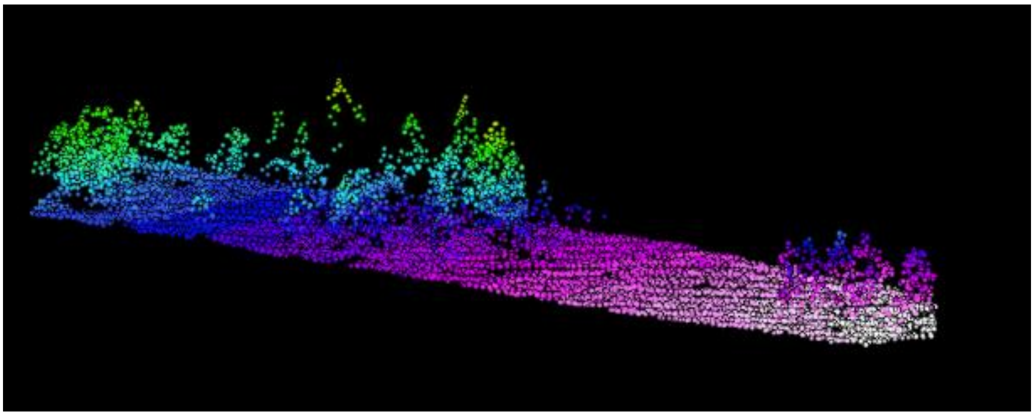


Figure 12. Example 100 x 25 m Lidar transect from the ARP showing a large forest opening (40.675°N, 105.516°W, elevation approximately 7920 ft.).

structure (Table 1), and are also an important component of monitoring wildlife habitat (see Section 5, below).

3.3.3 Considerations for using remotely measured metrics of forest structure

Data from Landsat and LIDAR provide useful tools for application to ARP forest plan monitoring. Through the Front Range CFLRP, over 500 variable radius plots have been installed between the ARP and the Pike San Isabel National Forests (Barrett et al. 2017) which can serve as a useful database for training, calibrating, and evaluating the accuracy of remotely measured metrics of forest structure. In addition, other CSE and FIA plots that have been collected on the forest can also be included as additional data for training and evaluation of remotely measured metrics from Landsat and LIDAR. The release of new tools such as LandsatLinkr and LandTrendr (see above) offer opportunities for the development of robust

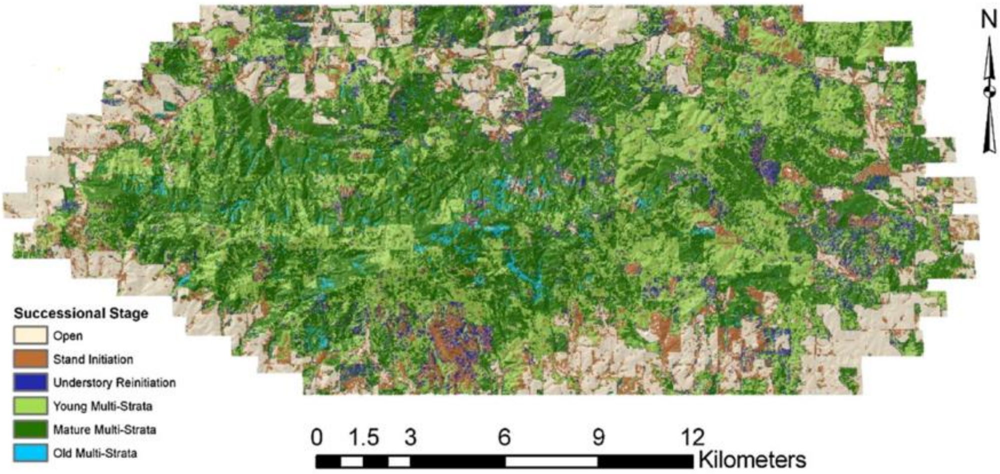


Figure 13. Classification of six successional stages of forest successional stages across a mixed-conifer forest in northern Idaho. Figure from Falkowski et al. (2009).

and consistent monitoring of forest structure across long temporal scales and large spatial scales.

The high-resolution Lidar data available in parts of the ARP (Figure 12) offers a unique opportunity for assessing baseline information on forest structure across a large portion of the ARP. However, in order to be most useful for assessing changes in forest structure over the 5- to 10-year time scales relevant for forest plan monitoring, additional LIDAR data can be periodically collected at repeated time intervals to measure changes over time. A recent estimate of the cost of collecting and analyzing LIDAR data and required training data (approximately \$2.29 to \$3.03 ac^{-1}) is comparable to the cost of collecting variable radius plots used in stand inventories (approximately \$2.46 ac^{-1}), and LIDAR-based inventories may be less expensive to conduct than traditional stand examines at larger spatial scales (e.g., 70,000+ acres).

4 FOREST WILDFIRE HAZARD AND WUI RISK

4.1 Introduction

The current ARP monitoring plan calls for assessing the status and trend of wildfire risk across the ARP with the stated goal to "reduce the number of high risk/high value, and high and moderate risk acres by 2,000 to 7,000 acres annually" using fuel reduction treatments (question 10). Within the Front Range CFLRP, there are no current efforts to assess the extent to which restoration treatments are effecting landscape-scale changes in fire hazard, risk, or disturbance regimes although stand-scale assessments of these changes have been evaluated (Addington et al. 2014). Recent discussions on evaluating changes in fire behavior at larger scales are being discussed within the CFLRP. Furthermore, CFRI is engaged with several partners to develop tools that address changes in landscape-scale fire risk that may have applications for ARP Forest planning.

There is considerable confusion about terminology used to communicate the potential for wildfire impacts to highly valued resources and assets (HVRAs) including "threat", "hazard", and "risk". Here, we adopt the definitions that "[h]azard is a physical situation with the potential to cause damage", whereas "risk further incorporates the likelihood that an HVRA will experience an event", consistent with the wildfire risk assessment framework being used by the USDA Forest Service and other US land management agencies (Scott et al. 2013). Hazard assessment focuses on the effects of fire if it were to occur on a discrete unit of the landscape at a given intensity. Risk assessment extends the products of hazard assessment to describe the expected effects from fire on a discrete unit of the landscape over a defined time period, calculated as the product of hazard and wildfire likelihood (Finney 2005).

Wildfire risk assessment is a rapidly-advancing discipline (Miller and Ager 2013), but some standard practices are emerging for land management applications (Scott et al. 2013). This section will demonstrate the application of the wildfire risk assessment framework (Scott et al. 2013) to Wildland Urban Interface (WUI) values in the Red Feather study landscape. Although this assessment will focus on a single value (WUI), the framework is designed to assess wildfire risk to multiple resources and assets in a consistent manner through a planning process that involves resource specialists and line officers, and thus is especially appropriate and applicable to forest planning.

Wildfire risk is defined as expected net value change (Finney 2005), and calculated as a function of wildfire likelihood and net value change (NVC) of a resource or asset exposed to a given fire intensity level (FIL). Wildfire risk assessment can therefore be compartmentalized into three general tasks: the first two involve using fire modeling to characterize wildfire likelihood and wildfire intensity, and the last involves quantifying the exposure and response of the highly valued resources and assets (HVRAs). There are a variety of tools that can be used for the fire modeling components, including FlamMap, Randig, and FSim (Finney 2006; Finney et al. 2011; Haas et al. 2015). HVRA exposure and response involves selecting the HVRAs to consider in the assessment, mapping the HVRAs, and defining response functions.

Wildfire likelihood is commonly quantified with burn probability modeling to estimate the relative or calibrated probability of experiencing wildfire in each pixel of a gridded fire modeling fuelscape. This is accomplished by simulating the spread of many wildfires across the fuelscape and tallying the number of fires that intersect each pixel. Burn probability can be relative (frequency of burning/total fires simulated) or calibrated depending on the fire modeling system used, the rigor with which simulation conditions are defined, and the use of post-modeling normalization techniques. It is important to understand the assumptions and limitations of burn probability modeling and specific burn probability modeling systems (Thompson and Calkin 2011; Miller and Ager 2013; Thompson et al. 2016).

Fire behavior metrics differ in their suitability for predicting fire effects for different HVRAs, but using a single metric simplifies the process when assessing risks to multiple HVRAs. The wildfire risk assessment framework advocates the use of six flame length categories to describe FIL because flame lengths are interpretable by most resource professionals (Scott et al. 2013). FIL can be characterized for one or more static fire weather conditions using the basic fire behavior metrics in FlamMap, or through simulation-based methods that capture variability in FIL due to fire spread direction and/or weather, depending on the fire modeling system used. For simulation-based methods, FIL is tallied each time a fire burns across a pixel and the resulting product is a conditional FIL distribution for each pixel in the fuelscape.

Resource exposure and response is the task of GIS analysts and resource specialists, who must decide what methods, are most appropriate for mapping the HVRAs and defining their response (or "susceptibility") to wildfire by FIL. Mapping can involve a variety of methods or datasets, but the products are typically a set of binary or categorical rasters that are co-registered with the fire modeling fuelscape rasters. Data are rarely available to quantitatively describe fire effects by FIL, so HVRA response is often characterized by expert response functions defined by the resource specialists (Scott et al. 2013). Such response functions describe how each resource under consideration may respond (positively or negatively) to various fire intensity levels. The wildfire risk assessment framework has the flexibility to add another layer of input from line officers in the form of relative HVRA importance values that can be used to weight the contributions of the HVRAs to the overall risk.

The final step in risk assessment is GIS analysis to calculate the expected NVC (eNVC) for each pixel in the fuelscape for the full suite of HVRAs. It is also common to produce HVRA-specific risk rasters to help interpret which HVRAs contribute to the overall risk and to support HVRA tradeoff analysis. The wildfire risk assessment framework (Scott et al. 2013) has primarily been used to support planning (e.g., Thompson et al. 2013a), but it is also well suited to monitoring. We present an example of how risk assessment products can be used to monitor fuel treatment risk reduction to WUI in the Red Feather Lakes study landscape.

4.2 Methods

It would be ideal to use FSim (Finney et al. 2011) to model the conditional FIL probabilities for the full distribution of fire weather conditions, however, FSim has not yet been distributed for public use. An excellent dataset of probabilistic wildfire risk assessment components modeled with FSim is available (Short et al. 2016) to support risk assessment for planning purposes, but it does not allow the post-treatment comparison necessary for monitoring. Thus, basic fire behavior modeling in FlamMap is used as a placeholder to demonstrate the process and the relevance of the outputs for addressing the monitoring questions relevant to forest planning.

Table 6. Fuel and weather parameters used for the fire behavior modeling in FlamMap, characterized using FireFamilyPlus for the Red Feather RAWS.

Percentile	Dead 1-hr moisture content	Dead 10-hr moisture content	Dead 100-hr moisture content	Live Herbaceous moisture content	Live Woody moisture content	Wind speed (mph @ 20 ft)	Converted 1 min wind speed (mph @ 20 ft)
80^{th}	4	5	9	25	60	13	18
90^{th}	3	4	8	7	60	16	21
97^{th}	2	3	7	4	60	22	27

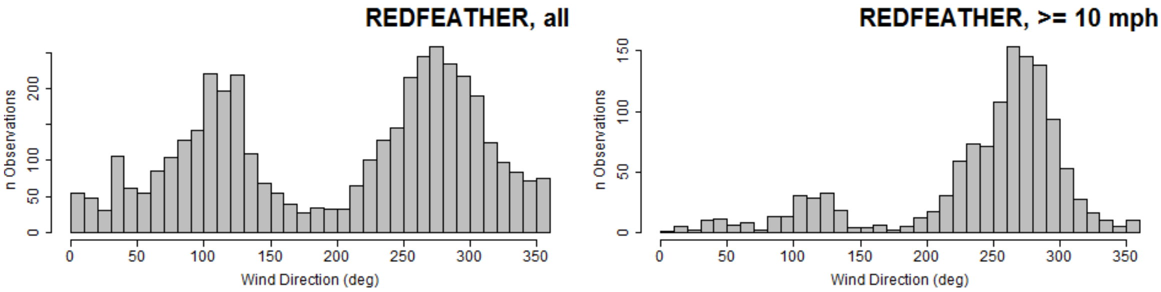


Figure 14. Wind direction distributions for the Red Feather RAWS station, considering all wind speeds (LEFT) and only wind speeds ≥ 10 mph @ 20 ft (RIGHT).

4.2.1 Wildfire likelihood

Wildfire likelihood is described by the National FSim Burn Probability Product (Short et al. 2016), modeled from 2012 LANDFIRE data using FSim (Finney et al. 2011). The 270-m resolution burn probability raster was resampled with bilinear interpolation to match the 30-m resolution of the fuelscape rasters used in the wildfire intensity modeling. No effect of fuel treatment on burn probability is modeled due to our use of pre-modeled outputs.

4.2.2 Wildfire intensity

We used FlamMap 5.0 (Finney 2006) to model flame lengths for a range of fuel and fire weather conditions. Fuel and fire weather conditions were summarized for the Red Feather Remote Automated Weather Station (station # 050505) using FireFamilyPlus 4.1 (Bradshaw and McCormick 2000) to characterize the 80th, 90th, and 97th fuel and fire weather conditions (Table 6) during the fire season (defined as April 1st through October 31st). Wind speed was converted to the 1 min average (Crosby and Chandler 1966), which is a better predictor of extreme fire behavior. Wind direction is quite variable when considering all wind speeds, but dominated by west winds for speeds ≥ 10 mph @ 20 ft. (Figure 14). We chose to use the fire burning uphill option with a default wind direction of 270 degrees in FlamMap to avoid underestimating the fire hazard on slopes sheltered from west winds.

4.2.3 Fuel treatment

Fuel treatment effects can be incorporated by simulating fuel reduction treatments in the baseline fuels data for the fire models. In this case, we do not examine the effect of a fuel treatment on burn probability because we acquired our burn probability estimates from another project (Short et al. 2016). Researchers have cautioned the use of fuel treatment for fire spread objectives (Reinhardt et al. 2008) and study of a similar landscape in west central Oregon estimated that a large fuel treatment program would reduce both fire size and annual area

Table 7. Treatment effects are applied to the modified LANDFIRE data as adjustment factors, e.g. an adjustment factor of 0.6 for mechanical only treatment on canopy bulk density (CBD) equates to a 40% reduction.

Canopy Parameter	**Mechanical Only**	**Mech + Rx Fire**	**Rx Fire Only**
CBD	0.6	0.5	0.92
CBH	1.2	1.2	1.09
CC	0.7	0.75	0.95
CH	1.2	1.2	1.13

burned less than a 10% (Thompson et al. 2013b). Fire modeling systems in the US use a set of co-registered rasters to describe surface and canopy fuels and topography. This data is commonly acquired from the LANDFIRE program (https://www.landfire.gov/) and then critiqued and updated for local conditions by a GIS analyst (Stratton 2009). We used the 2010 LANDFIRE release to characterize baseline conditions for assessing the effects of fuel treatments implemented between 2010 and 2014. The only adjustments we made to the baseline data were for lodgepole pine by lowering the canopy base height 20% and changing the fire behavior fuel model from TL3 to TL5 (Scott and Burgan 2005) to better reflect crown fire potential.

We simulated three different fuel treatment types – mechanical only, mechanical followed by prescribed fire, and prescribed fire only – based on effect sizes reported in the literature (Stephens and Moghaddas 2005; Stephens et al. 2009; Fulé et al. 2012; Ziegler et al. 2017). The fuel treatments are applied as adjustment factors (Table 7) to the LANDFIRE canopy variables. These generic fuel treatments were selected to illustrate the approach, but a more realistic workflow for assessment would include the measured effect sizes for each treatment unit from stand-scale estimates of treatment outcomes (see section 3 above)

Mechanical only treatments tend increase surface fuels, mechanical followed by prescribed fire treatments tend to keep fuel loads about the same, and prescribed fire only treatments decrease surface fuels (Stephens et al. 2009; Fulé et al. 2012). We make the conservative assumption that mechanical only treatments will increase the FBFM to higher rates of spread and flame lengths, unless the current FBFM is already the highest in the fuel model type (e.g. TL9 has the highest rates of spread and flame lengths in the TL fuel type). We assume that FBFM does not change with mechanical followed by prescribed fire because the surface fuel additions from the mechanical treatment are balanced with surface fuel reductions from the prescribed fire. We assume that prescribed fire will drop the FBFM down a category to lower rates of spread and flame lengths, unless the current FBFM is already the lowest in the fuel model type (e.g. TL1 has the lowest rates of spread and flame lengths in the TL fuel type). Only timber understory, timber litter, and slash-blowdown fuel types are assumed to have sufficient canopy fuels that can be transferred to the surface during implementation.

4.2.4 HVRA exposure and susceptibility

We used a high-resolution spatial database of structure locations (Caggiano et al. 2016) to represent WUI in this analysis. Spatial definitions of WUI have been a source of much controversy (i.e., Schoennagel et al. 2009), so we hope to emphasize that our use of this dataset was based on convenience and is not meant to replace the various spatial WUI layers used by the Forest for planning. The WUI structure database (Caggiano et al. 2016) consists of point

Table 8. WUI response function from Thompson et al. (2013) for the Lewis and Clark National Forest in Montana, including flame length ranges that define the FIL categories. Negative values indicate loss, whereas positive values indicate benefit from fire.

FIL	**1**	**2**	**3**	**4**	**5**	**6**
Flame length (ft)	< 2	2-4	4-6	6-8	8-12	> 12
Response	-10	-30	-60	-80	-100	-100

vector data of structure locations mapped from high-resolution aerial imagery using object-based detection methods. The WUI structure database contains 2,510 mapped structures within the Red Feather study landscape. We analyze three different spatial representations of this data: 1) a restricted definition of WUI, assigning pixel membership only to pixels that contain a WUI structure; 2) defining WUI as any pixel within a 0.5 km buffer around the structures; and 3) defining WUI as any pixel within a 1 km buffer around the structures.

The wildfire risk assessment framework can be used to assess a range of HVRA responses to wildfire, including positive effects when wildfire may restore or maintain fire adapted ecosystems (Scott et al. 2013). However, response functions for WUI are generally negative across the full range of FIL. We follow the WUI response function defined in Thompson et al. (2013a) for a wildfire risk assessment of the Lewis and Clark National Forest in Montana (Table 8). WUI losses are expected to increase steeply between flame lengths of 2 to 8 feet (Table 8).

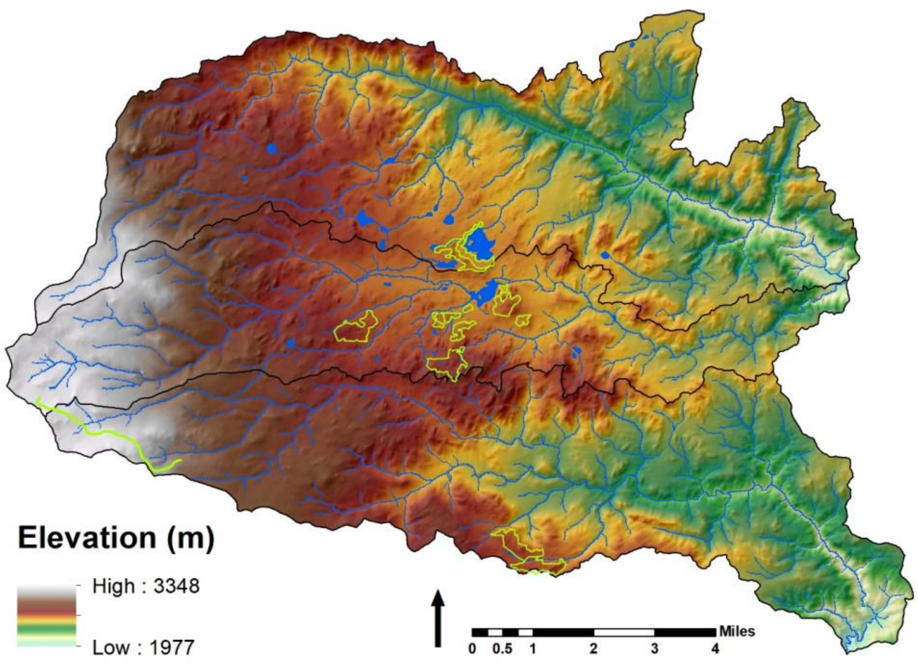


Figure 15. Pilot study landscape, consisting of three HUC12 watersheds in the Red Feather Lakes area. The bright green polygon boundaries delineate the 14 thinning and hazardous fuel reduction treatments implemented between 2010 and 2014.

4.3 Results

Wildfire risk to WUI was assessed for baseline (2010) and treated conditions (2014) for a study landscape near Red Feather Lakes, defined by the extent of three HUC12 watersheds (Elkhorn Creek, South Fork Lone Pine Creek, and North Fork Lone Pine Creek) covering approximately 64,000 acres (Figure 15). The effects of 14 pre-commercial thinning and thinning for hazardous fuels reduction treatments (Figure 15) totaling 833 acres were the target of the assessment, but these represent only a subset of fuel treatment activities completed in the study landscape.

4.3.1 Wildfire likelihood

Burn probability modeling results from Short et al. (2016) are presented for the study landscape in Figure 16. Mean annual burn probability for the study site ranges from zero for waterbodies to a high of 0.009, with a mean of 0.004. It may be surprising that the highest probability (most fire-prone pixel on the landscape) has an estimated annual burn probability of less than 1%, but it is important to recognize that there are many pixels in the landscape, so the annual probability of experiencing a fire in the study site is not the same as the maximum pixel value. The expected area burned is a more intuitive metric, which is calculated as the sum product of burn probability and pixel area for a zone of interest. The expected area burned for the study landscape is 274 ac yr^{-1}.

When estimating fuel treatment effects on risk, it is important to account for fuel treatment longevity (Rhodes and Baker 2008). However, because the response functions used here are based on relative values, there is no benefit to making this correction. If a similar framework were adopted for monitoring, there should be clearly defined criteria for the fuel treatments included as effective treatments (e.g. based on age of treatment or field monitoring of fuel conditions).

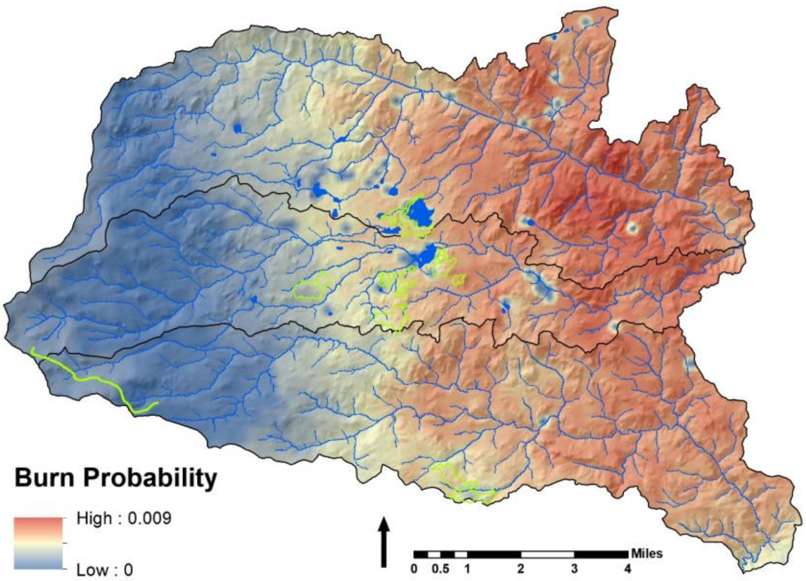


Figure 16. Mean annual burn probability from Short et al. 2016. Treatment boundaries are shown in bright green. Streams and waterbodies are shown in dark blue for reference.

4.3.2 Wildfire intensity

Modeled fuel treatment effects on fire intensity vary spatially depending on fuel treatment type, starting fuel conditions, topography, and fuel and fire weather conditions (Figure 17, Figure 18, and Figure 19). The simulated mechanical only treatment type includes the commonly observed increase in surface fuels (Stephens et al. 2009; Fulé et al. 2012), so flame lengths are predicted to increase with this treatment type under all percentile fuel and fire weather conditions, except in that case that treatment changes crown fire activity from crown to surface fire. The simulated mechanical followed by prescribed fire treatment leaves the fire behavior fuel model (FBFM; Scott and Burgan 2005) unchanged to reflect that surface fuel additions from the mechanical work are removed by prescribed fire, resulting in greater effects than the mechanical only treatment. The prescribed fire only treatment is simulated by minor changes in canopy variables and decreased surface fuel loads, represented here as a shift to a less active FBFM. The modeled prescribed fire only treatment therefore achieves the greatest fire intensity reduction of the three modeled fuel reduction treatments. These stylized fuel treatments are presented as examples to illustrate the process. These stylized treatment outcomes were developed based on existing literature and with input from B. Karchut (ARP, Fire and Aviation Staff Officer) and J. White (CL District, AFMO, Fuels). Ideally, these effects would be described by the fuels specialist for each treatment unit, based on field observations. Modeled

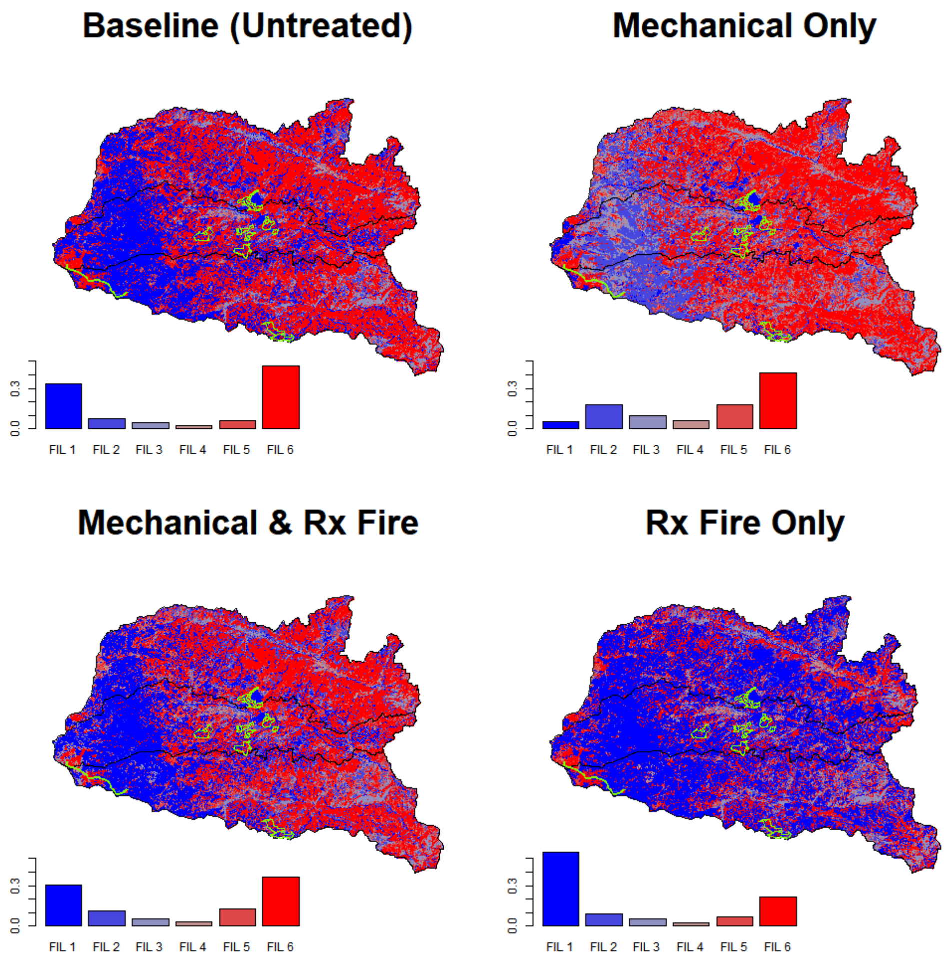


Figure 17. Fire intensity level (FIL) modeled using FlamMap for 80th percentile fire season conditions for untreated and treated scenarios. Note that no feasibility constraints were considered for the treated scenarios.

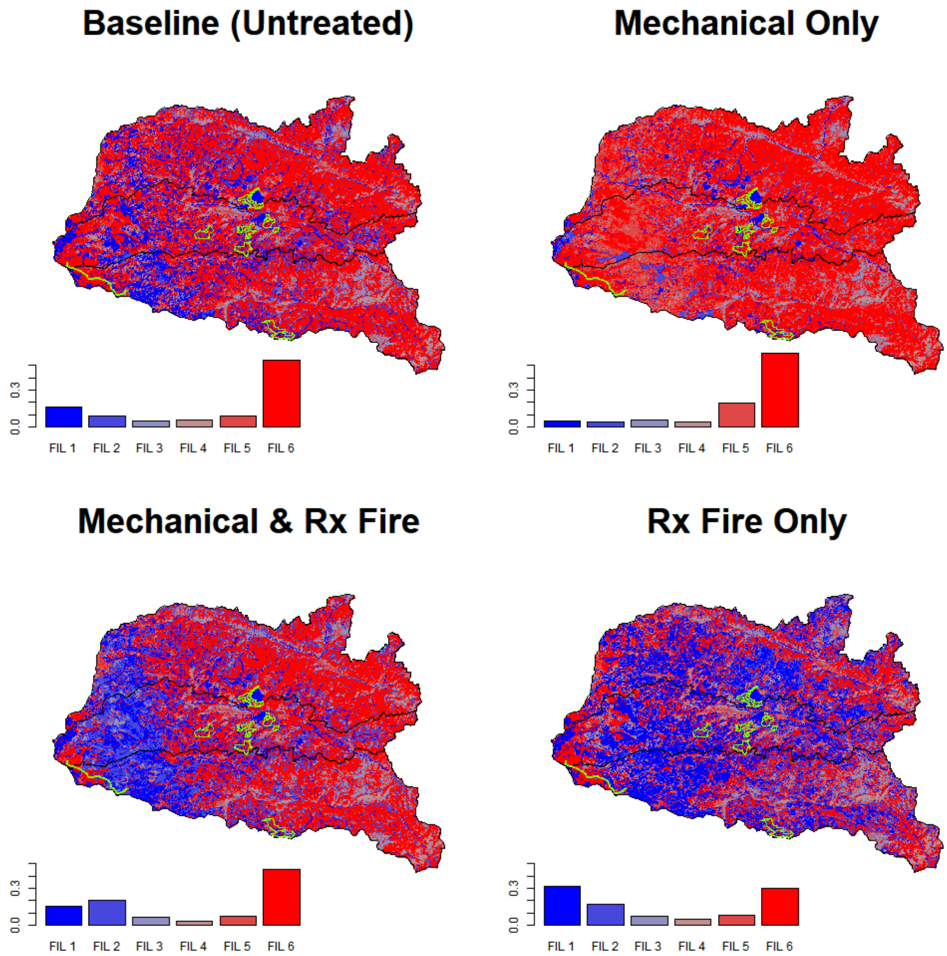


Figure 18. Fire intensity level (FIL) modeled using FlamMap for 90th percentile fire season conditions for untreated and treated scenarios. Note that no feasibility constraints were considered for the treated scenarios.

fuel treatments are most effective under less extreme fuel and fire weather conditions (Figure 17, Figure 18, and Figure 19).

4.3.3 Wildfire risk assessment

WUI extent is 479; 23,156; or 37,769 acres, respectively, depending on whether the restrictive definition, or 0.5 and 1 km buffer definitions are used (Figure 20). Only 2.2 acres of the 14 treatment units fall within WUI if the restrictive definition of WUI is adopted. Expanding the WUI extent increases the treated area in WUI to 338.5 and 664.1 acres.

WUI risk increases along a gradient from west to east and high to low elevation (Figure 20), driven by increasing burn probability (Figure 16) and fire intensity (Figure 17, Figure 18, and Figure 19). Much of the area at highest risk falls outside the National Forest ownership in ranches and exurban developments along Red Feather Lakes and Manhattan Roads in the eastern half of the study landscape. WUI risk in Beaver Meadows and Red Feather Lakes is low and moderate in comparison, primarily due to the lower likelihood of experiencing fire (Figure 16).

The current monitoring plan objective for wildfire risk is to “[r]educe the number of high risk/high value, and high and moderate risk acres by 2,000 to 7,000 acres annually” presents

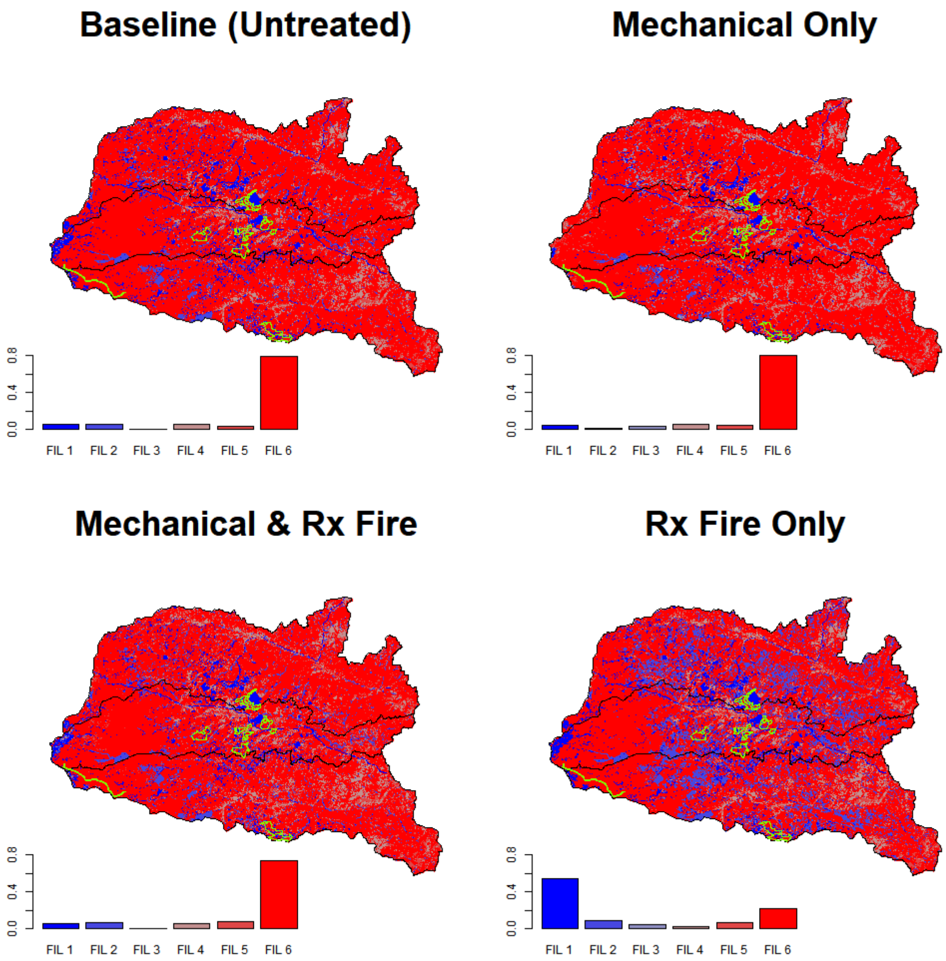


Figure 19. Fire intensity level (FIL) modeled using FlamMap for 97th percentile fire season conditions for untreated and treated scenarios. Note that no feasibility constraints were considered for the treated scenarios.

the total WUI area and area treated in each of seven risk categories, arbitrarily defined as equal intervals to divide the range of pixel eNVC values (same categories used in Figure 20). The area in each risk category changes across spatial definitions of WUI and fuel and fire weather conditions, but the most treated area generally falls in the lowest and middle risk classes (Table 10). It should be noted that this risk scale is relative and arbitrary. Since the majority of high-risk area in the study landscape is on private lands, the scale does not allow the National Forest much opportunity to address the highest risk areas; this may be an important point to address for both planning and monitoring.

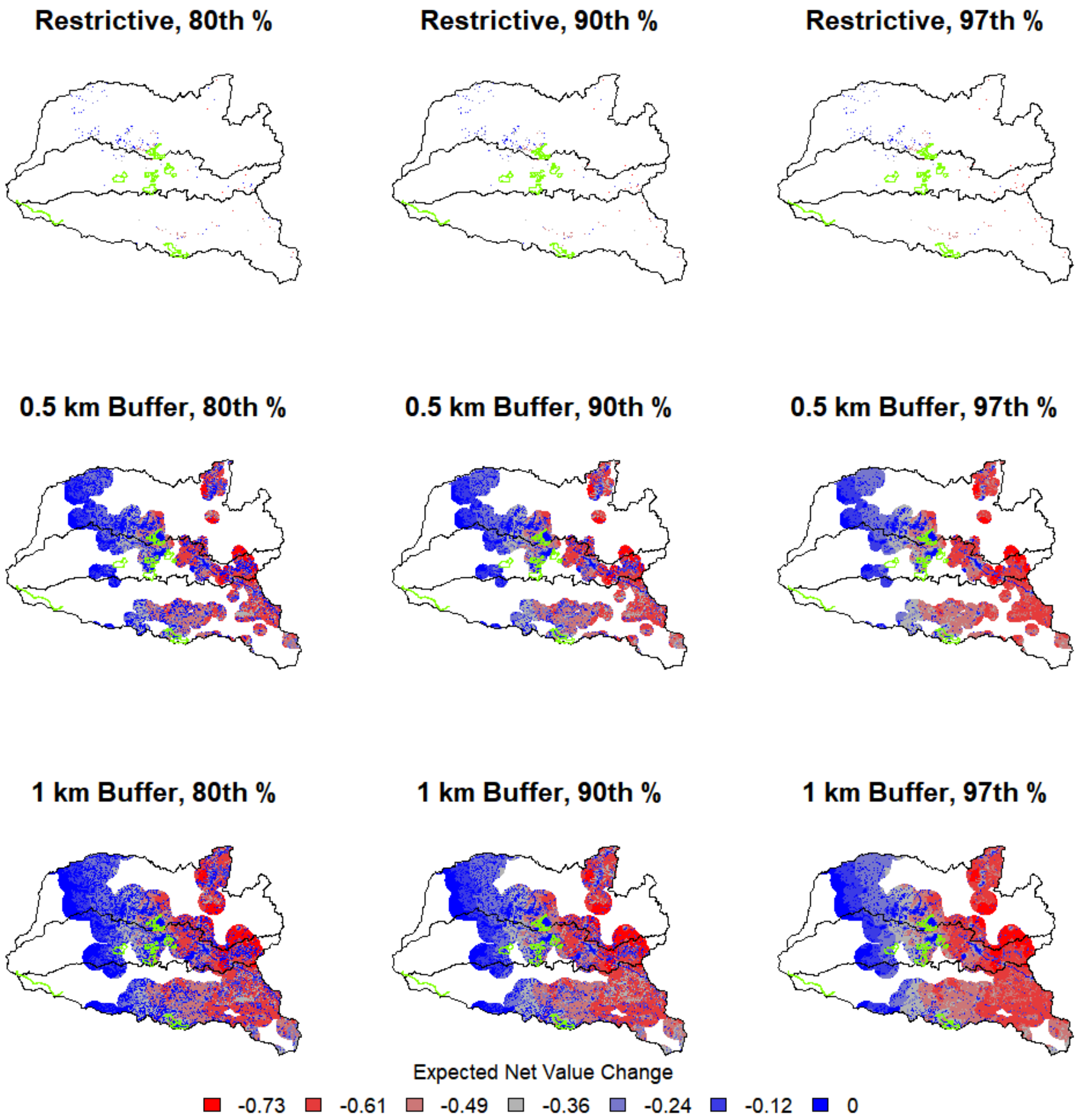


Figure 20. Baseline (untreated) WUI risk based on three different spatial definitions of the WUI and three different percentile fuel and fire weather conditions. Treatment boundaries are shown in bright green.

Table 9. Accounting of total risk for three different spatial definitions of the WUI and three fuel and weather conditions. Results are presented for the untreated (baseline) study landscape and the treated landscape with the 14 thinning and thinning for hazardous fuel treatment units (Figure 15) represented by the three stylized fuel reduction treatments described here. Risk is presented as expected Net Value Change. Consistent with the response function (Table 8), negative values represent loss, so risk reduction is achieved by moving risk metrics towards zero.

	Expected Net Value Change (Risk)		
	Restricted WUI	**0.5 km WUI Buffer**	**1 km WUI Buffer**
80th Percentile Fuel and Fire Weather Conditions			
Untreated	-670.8	-35,217.9	-58,670.6
Treated			
Mechanical Only	-671.8	-35,308.4	-58,867.8
Mechanical & Rx Fire	-670.9	-35,222.8	-58,677.6
Rx Fire Only	-669.6	-35,016.4	-58,357.1
90th Percentile Fuel and Fire Weather Conditions			
Untreated	-735.2	-39,245.4	-65,232.5
Treated			
Mechanical Only	-736.1	-39,325.8	-65,411.0
Mechanical & Rx Fire	-735.2	-39,237.8	-65,195.9
Rx Fire Only	-734.3	-39,063.8	-64,934.1
97th Percentile Fuel and Fire Weather Conditions			
Untreated	-824.6	-44,809.2	-74,243.0
Treated			
Mechanical Only	-825.0	-44,830.3	-74,292.1
Mechanical & Rx Fire	-824.6	-44,803.0	-74,224.8
Rx Fire Only	-824.6	-44,721.5	-74,093.7

The total effects of fuel treatments can be quantified by comparing risk for untreated and treated landscapes, using the fire intensity outputs with the simulated fuel reduction treatments (Table 9). The 14 pre-commercial thinning and thinning for hazardous fuels reduction treatments examined here (Figure 16) are best described as mechanical only treatments. Consistent with the earlier noted trend in FIL, this method estimates that losses will increase (more negative eNVC) by applying mechanical only treatment (Table 9). Results are also presented for the same area treated with mechanical followed by prescribed fire and prescribed fire only treatments (Table 9). The largest and most-consistently positive effects (reduced losses) are from the prescribed fire only treatment. The spatial definition of WUI, as well as the fuel and fire weather conditions, control the magnitude of total risk, which highlights the importance of consistent HVRA mapping and fire modeling conditions. The more specifically risk can be defined, the more useful risk assessment products will be for planning and monitoring.

4.4 Discussion

Wildfire risk assessment use for planning is growing in popularity, but there are also clear connections to monitoring. The current acres-based monitoring objective only requires a baseline risk assessment to spatially define the risk categories (Table 10). Implicit in the stated objective is the assumption that tracking the number of acres treated is sufficient to describe the benefit of treatment, i.e. the treated acres move out of the higher-risk categories. Although there are limitations with the fuel treatment simulation and fire intensity modeling methods we present here, it demonstrates a potential framework to measure risk reduction by accounting for treatment effects on fire intensity and the underlying wildfire likelihood. Treatment effects on fire intensity are highly variable depending on the starting forest conditions, the type and intensity of fuel treatment, the slash disposal methods, and the landscape context of the treatment. It may be overly optimistic to assume that every action categorized as a hazardous fuel treatment accomplishes the same effects (Figure 17, Figure 18, and Figure 19).

In the preceding analyses, we ignored fuel treatment effects on wildfire likelihood, mainly for logistical reasons, but researchers have strongly cautioned the use of fuel treatment for fire spread objectives (Reinhardt et al. 2008). It is possible that some fuel reduction treatments may actually accelerate fire ROS compared to pre-treatment, particularly for forest restoration treatments that promote understory development in what was previously a moderate-load timber-litter fuel type. A modeling study for a similar landscape in west central Oregon estimated that a large fuel treatment program would reduce both fire size and annual area burned less than 10%, and their assumptions were that fuel models transitioned to lower loads, lower ROS, and lower FL following treatment (Thompson et al. 2013a). The idea that fuel treatments will lower burn probability is often connected to the concept that fuel treatments will increase firefighter effectiveness. Of the US spatial fire modeling systems used for burn probability modeling, only FSim (Finney et al. 2011) simulates fire containment (Finney et al. 2009), so it would be the preferred tool to explore this question.

The extent of WUI (Figure 20) has significant implications for addressing the monitoring objective. With an inclusive definition of WUI (≥ 1 km of WUI HVRAs), most fuel treatment work done for any reason will count towards the WUI treatment objective. If judged by other metrics, such as the proportion of WUI treated, an inclusive definition of WUI may perform poorly, because the denominator will be very large. The choice of how to define WUI should be carefully considered, given recent critique of fuel treatment locations aimed at reducing wildfire risk to the WUI (Schoennagel et al. 2009). Although most home ignition research suggests fuels in the home ignition zone and building materials are more important than offsite wildland fuel treatments (Cohen 1995, 2000; Schoennagel et al. 2009), there is some evidence that wildland fuels up to 1 km from homes can contribute to home loss (Price and Bradstock 2013).

4.4.1 Limitations

FSim is ideal for modeling probabilistic wildfire likelihood and intensity components for risk assessment. We utilized a burn probability data product modeled with FSim (Short et al. 2016) to describe baseline conditions, but since we do not have access to the model, we could not produce an equivalent product for the post-treatment landscape. There are other tools for burn probability modeling, but none contain the same fire containment algorithm (Finney et al. 2009). FSim also captures a more realistic distribution of FIL by simulating fires over a wider range of fuel and weather conditions, generally leading to lower FIL than predicted for problem fire scenarios modeled using the basic fire behavior module in FlamMap (Thompson et al. 2016).

There is high variability in surface fuel characteristics following mechanical only treatment, but the trends point to increased surface fuel loadings and increased surface fire behavior (Stephens and Moghaddas 2005; Stephens et al. 2009; Fulé et al. 2012). However, our choice to simulate these effects by changing the categorical FBFM may overestimate the effects if the magnitudes of difference in fire behavior between FBFM are too large. Although several studies have confirmed the general trends, there are no commonly accepted methods for simulating increased surface fuel loads, especially for models that use categorical FBFMs. This has significant consequences for the estimated effects of the fuel reduction treatments, especially the mechanical only treatment type, which as described, increases risk.

We used a readily-accessible dataset (Caggiano et al. 2016) to define WUI for this analysis, that may not match WUI data products used by the Forest. To be consistent with the wildfire risk assessment framework (Scott et al. 2013) and the risk assessment we borrowed the WUI response function from (Thompson et al. 2013a), we mapped only the presence and absence of WUI. This is appropriate for large landscape- to regional-scales, but for a smaller extents and more focused analysis, it may be desirable to consider the density and/or values of the homes to more precisely define risk.

Despite these limitations, the framework and datasets outlined above, provide a robust framework for analyzing the effects of forest management practices on changes to WUI risk. Such analyses can be used to better understand the status and distribution of WUI risk across the ARP for planning purposes. Combined with a treatment simulation process similar to that above, these analyses can serve a critical function of evaluating landscape scale effects of management practices on WUI risk at the ARP.

5 PROTECTION OF SOIL AND WATER RESOURCES

5.1 Introduction

Within the Front Range CFLRP, there are no active efforts to assess the extent to which restoration treatments are effecting landscape-scale changes to soil and water resources, although some landscape-scale approaches are currently being considered. CFRI is engaged with several partners to develop tools that address changes in landscape-scale fire risk that may have applications for ARP Forest planning. Here, we demonstrate a linked model approach to monitor forest management practices on watershed health regarding erosion and runoff. The linked model approach combines wildfire, erosion, and sediment transport models to estimate the hazard and risk reduction of wildfire-related erosion and sediment delivery to streams. We use the definition of wildfire risk as outlined in Scott et al. (2013) and in section 4.1 above.

The linked model approach uses fire models to describe wildfire likelihood and behavior, and erosion and sediment transport models to describe resource exposure and response at two different scales (Figure 21). The framework is flexible, allowing for configurations that could support assessment, planning, or both. The effects of forest management actions are incorporated by simulating fuel reduction treatments on the baseline fuels data that go into the fire behavior model, so that treatment effects can be quantified as the difference between untreated and treated landscapes.

5.2 Methods

5.2.1 Wildfire likelihood

Most wildfire risk assessments use burn probability modeling to estimate the likelihood of experiencing fire across a landscape based on the current configuration of fuels and some representation of ignition likelihood and fire weather conditions (Scott et al. 2013). There are

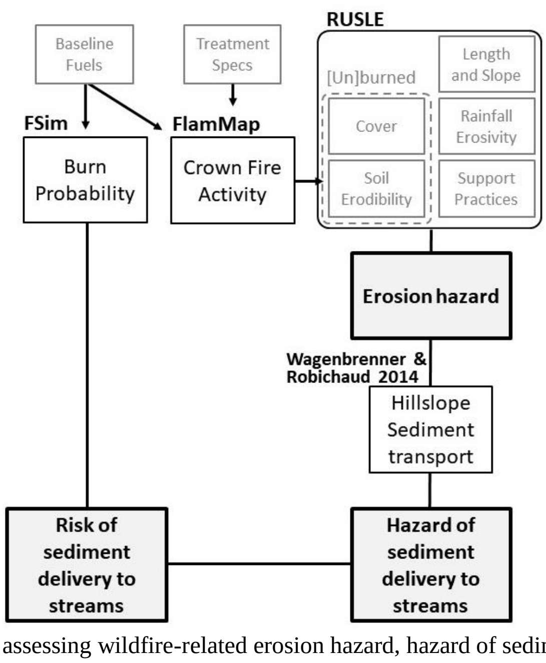


Figure 21. Model framework for assessing wildfire-related erosion hazard, hazard of sediment delivery to streams, and risk of sediment delivery to streams.

Table 11. Fuel and weather parameters used for the fire behavior modeling in FlamMap, characterized using FireFamilyPlus for the Red Feather RAWS for the 97th percentile fire season conditions.

Dead 1-hr moisture content	Dead 10-hr moisture content	Dead 100-hr moisture content	Live Herbaceous moisture content	Live Woody moisture content	Wind speed (mph @ 20 ft)	Converted 1 min wind speed (mph @ 20 ft)
2	3	7	4	60	22	27

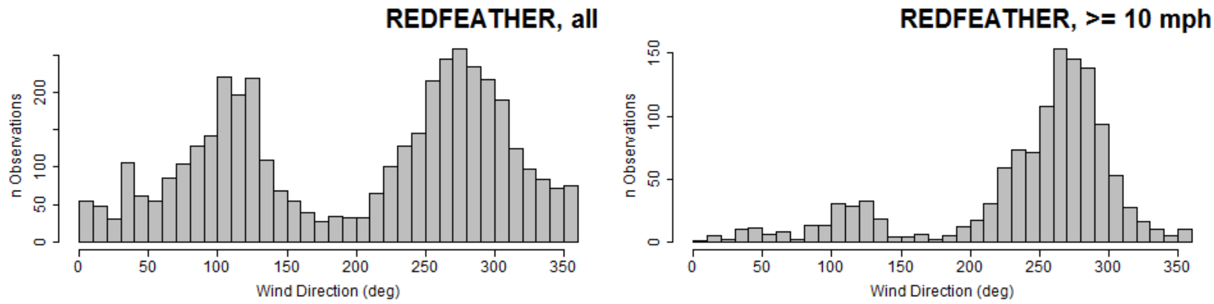


Figure 22. Wind direction distributions for the Red Feather RAWS station, considering all wind speeds (LEFT) and only wind speeds ≥ 10 mph @ 20 ft (RIGHT).

many assumptions that go into the burn probability modeling process, so rather than completing our own custom modeling, we utilized the National FSim Burn Probability Product (Short et al. 2016), modeled from 2012 LANDFIRE data using the Large Fire Simulator (FSim; Finney et al. 2011).

5.2.2 Fire behavior

We used FlamMap 5.0 (Finney 2006) to model crown fire activity (Scott and Reinhardt 2001) as an index of fire severity, similar to studies of wildfire-debris flow risk (Tillery et al. 2014; Thompson et al. 2016; Tillery and Haas 2016), by mapping surface, passive crown, and active crown fire to low, moderate, and high severity. This simplifying assumption is reasonable, given that most wildfire effects on erosion are only described at the resolution of low, moderate, and high severity, but there is also considerable opportunity to improve this part of the model framework in the future by using a continuous measure of fire severity.

Most area burned during recent decades in the Colorado Front Range is the product of large fire events that occur during extreme fire weather conditions, so we modeled crown fire activity for 97th percentile fire weather conditions from the Red Feather Remote Automated Weather Station (station # 050505). The fuel and fire weather conditions were summarized using FireFamilyPlus 4.1 (Bradshaw and McCormick 2000) to characterize the 97th conditions (Table 11) during the fire season (defined as April 1st through October 31st). Wind speed was converted to the 1 min average (Crosby and Chandler 1966), which is a better predictor of extreme fire behavior. Wind direction is quite variable when considering all wind speeds, but dominated by west winds for speeds ≥ 10 mph at 20 ft. (Figure 22). We chose to use the fire burning uphill option with a default wind direction of 270 degrees in FlamMap to avoid underestimating the fire hazard on slopes sheltered from west winds.

5.2.3 Fuel treatments

See section 4.2.3 above for a description of fuel treatments simulation details. We use the same methods here to simulate fuel reduction treatments using in the baseline fuels data acquired from the LANDFIRE program (http://www.landfire.gov). These data were critiqued and for local conditions (Stratton 2009). We simulated three different fuel treatment types – mechanical only, mechanical followed by prescribed fire, and prescribed fire only – based on effect sizes reported in the literature (Stephens and Moghaddas 2005; Fulé et al. 2012; Ziegler et al. 2017). See section 4.2.3 above for full description.

5.2.4 Resource exposure and response

Watershed response is modeled in two ways: 1) local soil loss rate (erosion) for each 30 m pixel in the landscape using a GIS implementation of the Revised Universal Soil Loss Equation (RUSLE; Renard et al. 1997) and 2) sediment delivered to the channel network from each 30 m pixel using a hillslope sediment transport model (Wagenbrenner and Robichaud 2014).

5.2.5 Erosion

The RUSLE (Renard et al. 1997) consists of five subfactors that are multiplied together to calculate the predicted annual soil loss (A). The subfactors are rainfall-runoff erosivity (R), soil erodibility (K), length-slope (LS), cover-management (C), and support practices (P). Annual soil loss is calculated by multiplying the five subfactors, as follows:

$$A = R * K * LS * C * P$$

where

A = estimated average soil loss in tons acre^{-1} year^{-1}

R = rainfall-runoff erosivity factor

K = soil erodibility factor

LS = length-slope factor

C = cover-management factor

P = support practice factor (ignored)

Support practices generally refer to agricultural interventions such as tilling and buffer strips. In forestlands, there are limited to no management interventions of this type, so no support practice factor was modeled.

We followed the GIS-based implementation of RUSLE described in Theobald et al. (2010) with minor modifications. Similar approaches have been used for post-fire hazard assessment of the High Park and West Fork Complex Fires in Colorado (Yochum and Norman 2015) and for forecasting erosion under different climate change scenarios in the Southern Rockies Ecoregion (Litschert et al. 2014). For a complete review of the methods see Theobald et al. (2010).

- **R Factor** – The rainfall-runoff erosivity factor (R) is an annual metric of rainfall that integrates total rainfall energy and maximum 30 min intensity. Greater than 95% of annual sediment yield is mobilized by summer rainstorms in the period from June through October

(Larsen and MacDonald 2007), so we summed the 30 year normal monthly precipitation data from PRISM (http://www.prism.oregonstate.edu/) from June through October and used the Renard and Freimund (1994) equations to calculate erosivity. PRISM data has a resolution of 800 m, so the final product was resampled with bilinear interpolation to match the 30 m resolution of other data layers.

- **K Factor** – The soil erodibility factor (K) is the rate of soil loss per rainfall erosion index unit (Renard et al. 1997) and is generally determined empirically, or sometimes using equations based on soil texture. The K factor is an attribute recorded in the national cooperative soil survey data maintained and distributed by USDA Natural Resources Conservation Service (NRCS). Soils data for the project area includes coverage from the higher-resolution Soil Survey Geographic Database (SSURGO) and the coarser-resolution State Soils Geographic Database (STATSGO). We used the whole soil K factor (kwfact) which is adjusted for the effect of rock fragments and attributed at the horizon level. In both SSURGO and STATSGO, map units are made up of multiple components with specified percent cover and components are made up of multiple horizons with specified depth. We followed the methods of Yochum and Norman (2015) to calculate the K factor for each component as the depth-weighted mean for each horizon in the top 15 cm of the soil profile and for each map unit as the area-weighted mean of all non-water and non-rock component types. SSURGO data was used preferentially due to its higher resolution, but it was gap-filled as needed with STATSGO for map units missing K factor data. The complete project coverage of SSURGO and STATSGO map unit polygons were converted to a 30 m raster to match the resolution of the other data layers.
- **LS Factor** – The length-slope factor (LS) is the product of the slope length factor (L) and the slope steepness factor (S), which together represent the influence of topography on erosion and are discussed jointly here because they are calculated in a single process from a 30 m DEM. The original intent for the RUSLE was for these factors to be measured in the field, but numerous GIS adaptations of USLE/RUSLE can be used to approximate LS across large landscapes. We follow the methods of Theobald et al. (2010), Litschert et al. (2014), and Yochum and Norman (2015) to calculate LS with two modifications: 1) a flow accumulation threshold was applied to approximate the hillslope length limit (~1,000 ft), and 2) we constrained the final LS factor values to the maximum from Renard et al. (1997). The LS factor output was reprojected and resampled to co-register with other data layers.
- **C Factor** – The cover-management factor (C) was mapped to the existing vegetation type (EVT) from LANDFIRE using values assembled in Yochum and Norman (2015) and Litschert et al. (2014). The barren EVT, which has a very high C factor value, is assigned to some alpine areas that have low rates of erosion (S. Kampf, personal communication), so barren areas ≥ 2900 m were reassigned a C factor of zero.

5.2.6 Integrating fire behavior results

The primary drivers of post-wildfire erosion (ignoring rainfall characteristics) are reduced vegetation cover and changes to the physical and chemical characteristics of soils (Neary et al. 2005; Shakesby and Doerr 2006). Post-fire erosion response can be modeled by mapping fire severity to changes in the RUSLE cover factor (C) and soil erodibility factor (K) using local data (Larsen and MacDonald 2007; Schmeer 2014; Yochum and Norman 2015).

For forested areas (> 10% canopy cover in LANDFIRE), we assign the mean C factor values for the first year after burning from Larsen and MacDonald (2007) using a remap table (Table

Table 12. Mean cover factor values from Larsen and MacDonald (2007) calculated from nine wildfires in the Colorado Front Range. C factor values are applied as a remap to forests (> 10% canopy cover in LANDFIRE). Cover factor effect sizes applied as multiplication factors for non-forest vegetation types (≤ 10% canopy cover). Soil erodibility factor effect sizes applied as multiplication factors, from Schmeer 2014.

CFA Value	Fire Severity	C Factor Remap for forest	C Factor Effect for non-forest	K Factor Effect
1 (surface)	Low	0.01	1.2	1.5
2 (passive)	Moderate	0.05	1.5	1.75
3 (active)	High	0.20	2.0	2.0

12). For areas with < 10% canopy cover (non-forest) we applied a set of effect sizes (multiplication factors) to estimate post-fire C factor (Table 12). These effect sizes are conservative compared to the ~ 100x increase in cover factor for forested areas burned at high severity. Effect sizes are used due to the diversity of non-forest vegetation types and the limited post-fire erosion work in these systems (see Pierson et al. 2016 for discussion).

There are some slight mismatches between EVT forest classes and the 10% canopy cover threshold, so any "improved" pixels were replaced with their original values. We expect that these very low-density forest vegetation types would be minimally impacted by fire and they also represent a very small fraction of the landscape.

Fire effects on soils are diverse, but generally lead to decreased infiltration and cohesion, from a range of processes including deposition of hydrophobic compounds, soil sealing, and consumption of organic material (Neary et al. 2005; Shakesby and Doerr 2006). Quantitative measure of post-fire K factors is lacking, but Larsen and MacDonald (2007) back-calculate an effect size of 2.5 for high severity. Given the assumptions of this methodology, we adopted the more conservative values (Table 12) used in Schmeer (2014).

Other RULSE factors (rainfall erosivity and length-slope) are unchanged by fire.

5.2.7 Sediment transport

The RUSLE soil loss rates can be converted to the mass of sediment delivered from each pixel to the channel network using an empirical model of post-fire sediment delivery ratio (SDR) from watersheds burned in the western US, including Colorado (Wagenbrenner and Robichaud 2014). SDR is modeled for each pixel using the annual length ratio equation (Wagenbrenner and Robichaud 2014), where the flow path length across the pixel is treated as the small catchment length and the flow path length to the nearest channel is treated as the larger catchment length. The channel network was defined as the medium resolution National Hydrography Dataset flowlines (NHDPlus), plus an extension using the mean contributing area for channel head formation in the Front Range from Henkle et al. (2011) as a flow accumulation threshold. SDR in this model can vary between 0 and 1 and can be used as a multiplier to scale the gross erosion at the 30 m pixel-scale to the sediment delivered to the stream.

5.3 Results

Baseline (2010) hazard and risk of erosion and sediment delivery to streams were assessed for three HUC12 watersheds in the Red Feather Lakes area (Elkhorn Creek, South Fork Lone Pine Creek, and North Fork Lone Pine Creek) covering approximately 64,000 acres (Figure 24).

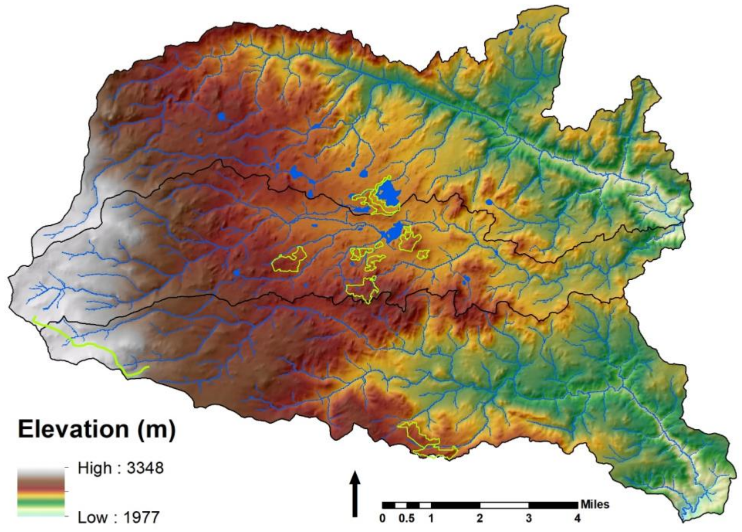


Figure 24. Pilot study landscape, consisting of three HUC12 watersheds in the Red Feather Lakes area. The bright green polygon boundaries delineate the 14 thinning and hazardous fuel reduction treatments implemented between 2010 and 2014.

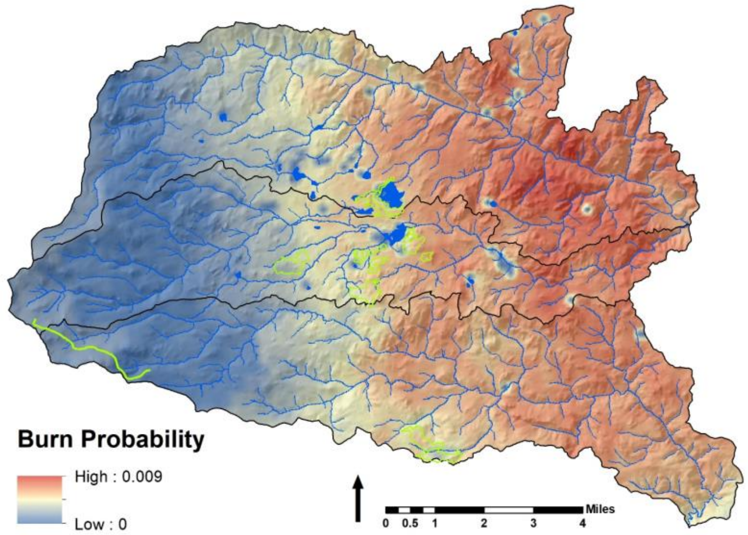


Figure 23. Mean annual burn probability from Short et al. 2016. Treatment boundaries are shown in bright green. The channel network (dark blue) is an extension (Henkle et al. 2011) of the NHDPlus medium resolution flowlines.

The effects of 14 pre-commercial thinning and thinning for hazardous fuels reduction treatments (Figure 24) totaling 833 acres were assessed by comparing hazard and risk of erosion and sediment delivery for treated and untreated landscapes.

5.3.1 Wildfire likelihood

Burn probability modeling results from Short et al. (2016) are presented for the study site in Figure 23. Mean annual burn probability for the study site ranges from zero for waterbodies to a high of 0.009, with a mean of 0.004. It may be surprising that the highest probability (most fire-prone pixel on the landscape) has an estimated annual burn probability of less than 1%, but it is important to recognize that there are many pixels in the landscape, so the annual probability of experiencing a fire in the study site is not the same as the maximum pixel value. The expected area burned is sometimes a more intuitive metric, which is calculated as the sum product of burn probability and pixel area for a zone of interest. The expected area burned for the study landscape is 274 acre yr^{-1}. Unpublished analysis from CFRI confirms that the Short et al. (2016) burn probability estimates are very close to the Front Range-wide mean annual burn probability calculated from MTBS data from the modern era (1984-2015).

When estimating risk reduction from fuel treatment, it is important to correct annual burn probability to burn probability over the effective lifespan of the fuel treatment (Rhodes and Baker 2008). For risk assessment calculations, we assume fuel treatments have constant effectiveness for 25 years, and correct to the probability of experiencing fire over *n* years, *q*, as a function of annual burn probability *p* using equation 1.

$$q = 1 - (1 - p)^n \qquad \textbf{Eqn. 1}$$

5.3.2 Fire behavior

Modeled fuel treatment effects on fire behavior vary spatially depending on fuel treatment type, starting fuel conditions, and topography (

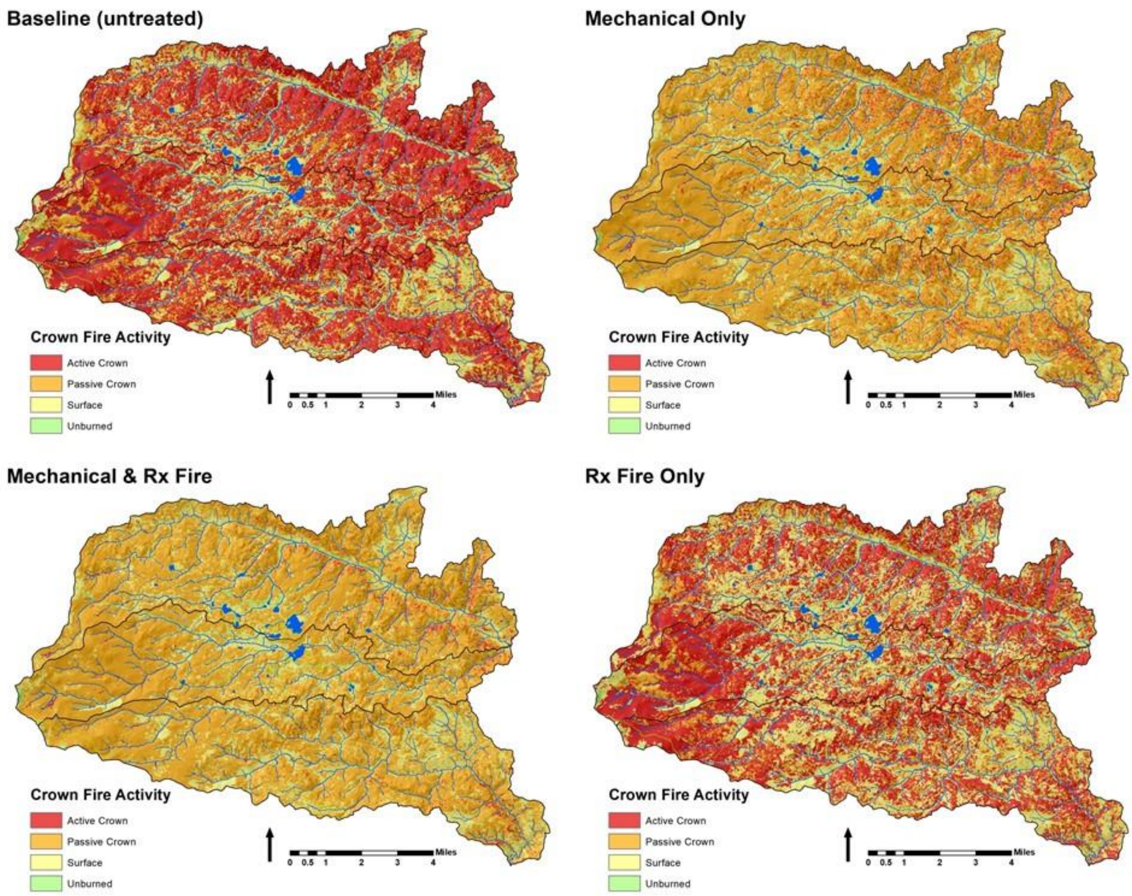


Figure 25. Crown fire activity output from FlamMap for 97th percentile fire weather conditions for the baseline (UPPER LEFT), mechanical only treatment (UPPER RIGHT), mechanical and Rx fire treatment (LOWER LEFT), and Rx fire only treatment (LOWER RIGHT) scenarios. NOTE: all pixels are treated in the three treatment scenarios without regard for feasibility to illustrate the variability in fuel treatment effects across the landscape.

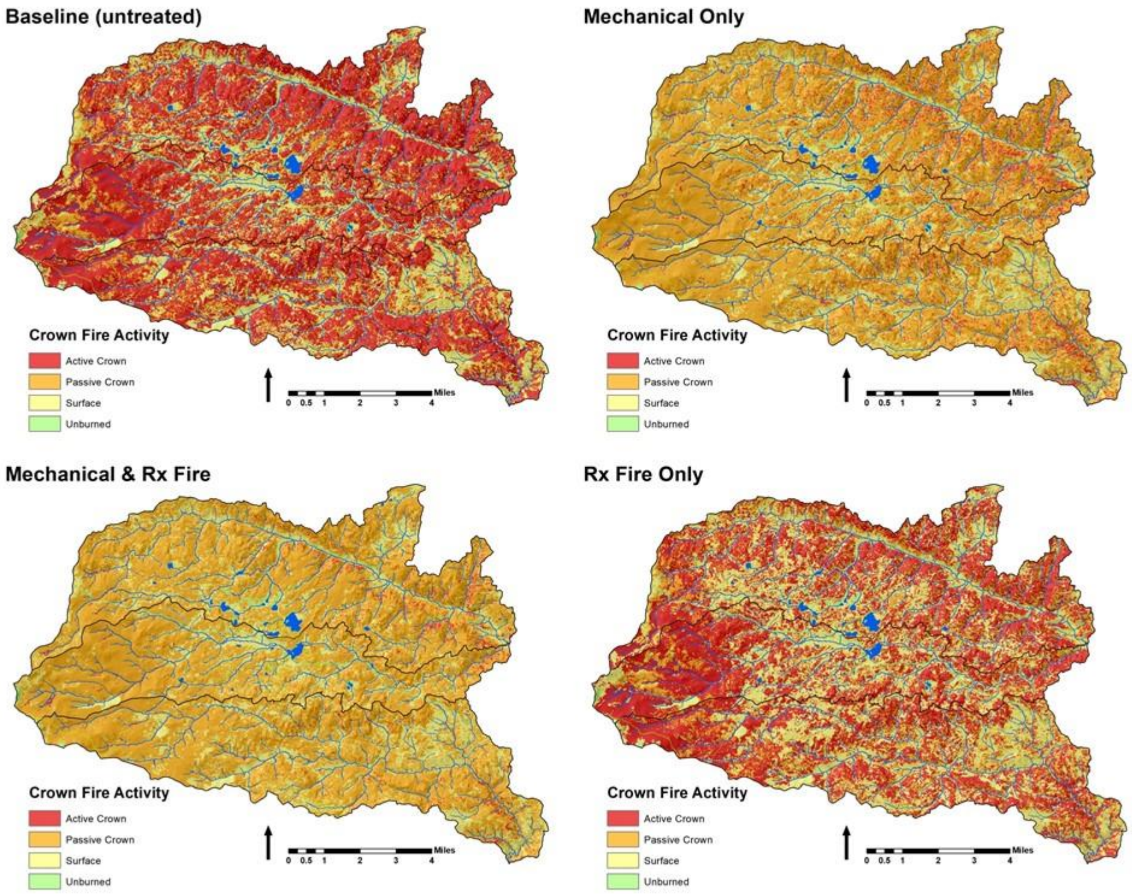


Figure 25). Under 97th percentile conditions, most of the untreated study site is expected to produce active crown fire behavior. The modeled mechanical only and mechanical followed by prescribed fire treatments are generally effective at moving active crown fire to passive, and in some cases moving passive crown fire to surface fire (

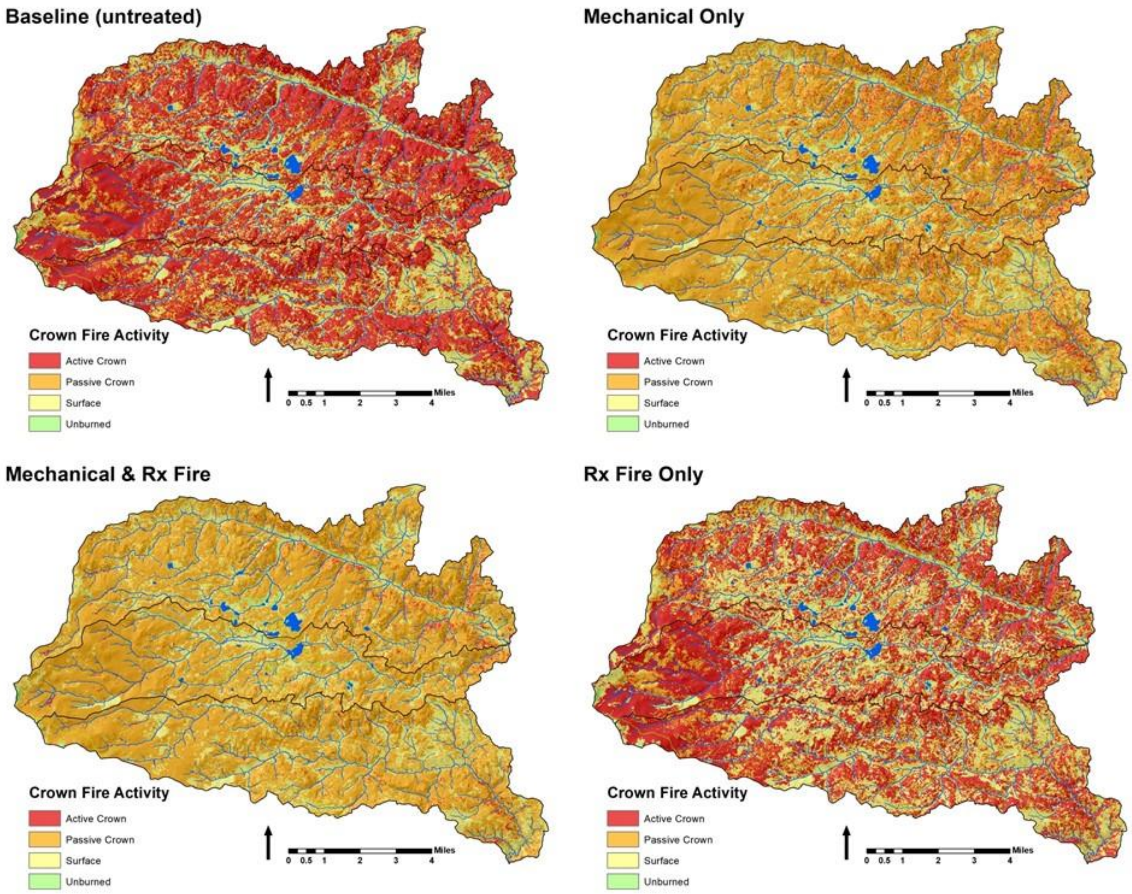


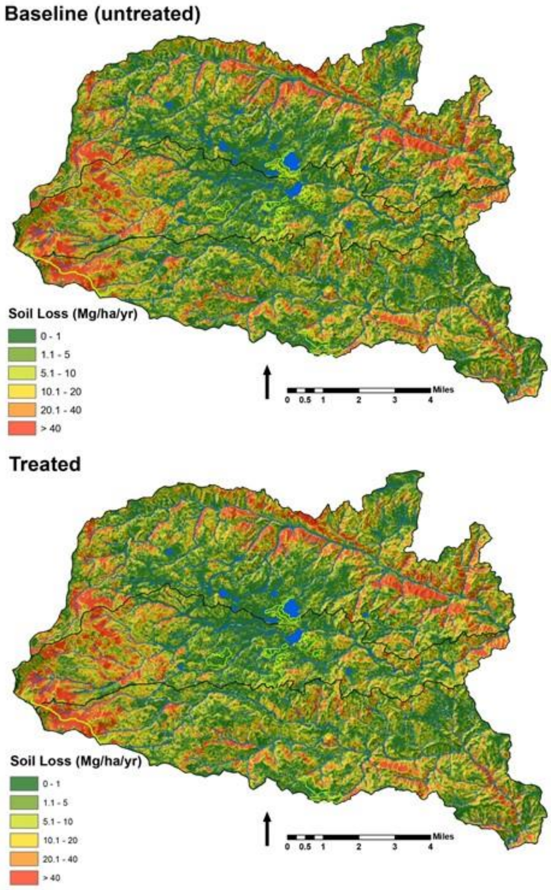
Figure 25). There are some limited places where the modeled mechanical followed by prescribed fire treatment is more effective than mechanical only treatment; it is important to recognize that the minor difference captured here is due to the limited resolution of a four-class ordinal variable (CFA), and is not meant to suggest there is low value of following up with prescribed fire. The prescribed fire only treatment is less effective than the mechanical treatments, as modeled, but it often costs less, so it can sometimes look more attractive using a metric like benefit-cost ratio.

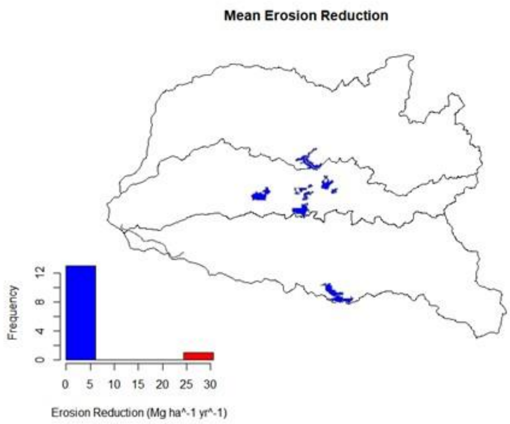
5.3.3 Erosion

Modeled fuel treatment effects on erosion vary based on treatment effects on fire behavior, layered on top of variability in erosion due to soils and topography (Figure 26). The study landscape is one of the lower-relief areas of the ARP, and since steep slopes are most-erodible, nearly 70% of the study area is expected to have erosion rates < 10 Mg ha^{-1} in the 1st year post-fire (sometimes called year 0) and less than 8% of the landscape is expected to have erosion rates > 40 Mg ha^{-1}. The highest-erosion hazard areas are steep and densely vegetated, associated with canyon walls at lower elevations and the slopes of the Bald Mountains. Like effects on fire behavior, mechanical and mechanical followed by prescribed fire treatments tend to be very effective at reducing erosion hazard, whereas prescribed fire only treatment has lower effectiveness.

5.3.4 Fuel treatment effects on erosion hazard

It is assumed that the 14 pre-commercial thinning and thinning for hazardous fuels reduction treatment effects are best described by the modeled mechanical only fuel treatment. The landscape-scale total erosion hazard is not significantly altered by the fuel treatments (Figure





Mean Erosion Rate (Mg/ha/yr)				
Treatment Unit	Pre-treatment	Post-treatment	Reduction	Percent Reduction
4	64.4	33.8	30.6	47.5
7	9.5	3.6	5.9	61.9
13	9.5	3.8	5.7	60.1
8	7.7	2.6	5.1	65.9
12	6.7	2.9	3.7	56.3
3	6.1	2.5	3.6	59.7
6	6.2	2.6	3.6	58.3
2	5.6	2.1	3.5	62.4
5	5.0	1.6	3.5	69.0
1	3.1	1.2	1.9	62.6
11	2.3	0.8	1.4	62.8
10	2.2	0.9	1.3	58.5
14	2.1	1.1	1.0	47.8
9	1.2	0.4	0.8	64.3

Figure 27. Erosion hazard for pre- and post-treatment landscapes with application of the 14 mechanical only treatments. The pre-treatment 1st year erosion rate (UPPER LEFT) can be contrasted with the post-treatment 1st year erosion rate (LOWER LEFT). To highlight the effect of treatment, the mean erosion rate reduction was calculated for each treatment unit (UPPER RIGHT and LOWER RIGHT).

treatment effects across the landscape.

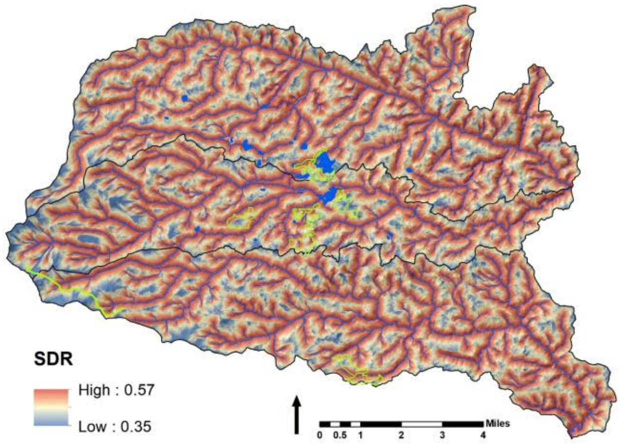


Figure 28. Hillslope sediment delivery ratio (SDR) calculated using the annual length ratio model from Wagenbrenner and Robichaud 2014. The channel network and lakes are shown in dark blue. Treatment boundaries are shown in bright green.

27) which is not surprising given that the treated area amounts to only 1.3% of the landscape and the fuel treatments locations were probably not prioritized to reduce erosion. Even though these 14 thinning treatments were not optimally-located to reduce erosion hazard, they are expected to decrease erosion hazard, in the range of 0.8–30.6 Mg ha^{-1}, or 47.5–69.0% in the 1st year post-fire within the areas treated. Treatment unit 4, which is the roadside treatment in the western corner of the study landscape, has the highest estimated hazard reduction of 30.6 Mg ha^{-1} in the 1st year post-fire. Hazard does not include wildfire likelihood, which is estimated to be lower at this elevation compared to the other thinning treatments (Figure 23).

5.3.5 Sediment transport

The Wagenbrenner and Robichaud (2014) annual length ratio model predicts sediment delivery ratios ranging from 0.35–0.57 for uplands (Figure 28). Hillslope SDR can be used to scale gross erosion produced in each pixel (RUSLE A) to what is delivered to the channel network using Equation 2.

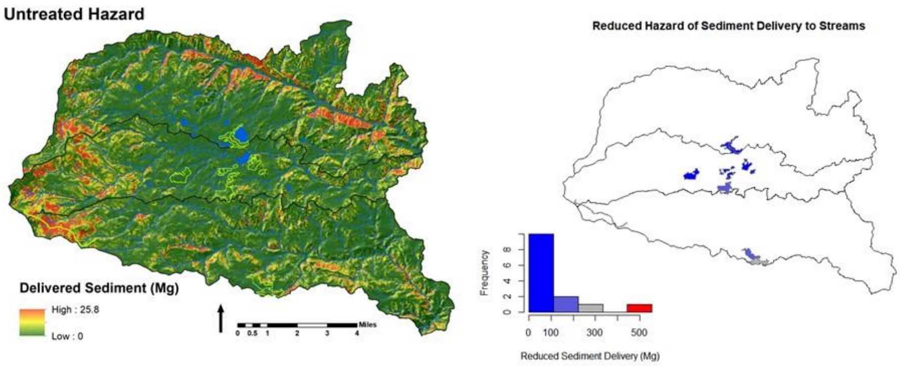
$$Sediment\ Delivered = A * Area_{Cell} * SDR \qquad \textbf{Eqn. 2}$$

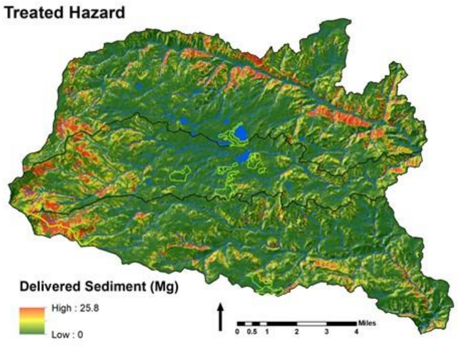
5.3.6 Hazard of sediment delivery to streams

The hazard of wildfire-related sediment delivered to streams depends on sediment transport (Figure 28), placing stronger emphasis on areas with shorter flow paths to streams (Figure 29). Hazard here is measured as the wildfire-related increase in sediment delivered (Mg) over unburned conditions, corrected for the multiple post-fire years of elevated erosion (Pietrazek 2006). Hazard of sediment delivery to streams is concentrated in a few canyons, especially North Lone Pine Creek, as well as the high slopes of the Bald Mountains. The maximum estimated pixel-level sediment delivery hazard is 25.8 Mg, which should be interpreted as the fire-related increase in sediment produced from that pixel delivered to streams over the entire period of elevated post fire erosion. The range of hazard reduction from the 14 thinning treatments is 3.2–556.2 Mg or 48.0–69.5%, and it is estimated that the combined effect of all thinning treatments is a reduction of 1,612.9 Mg of sediment delivered to streams.

5.3.7 Risk of sediment delivery to streams

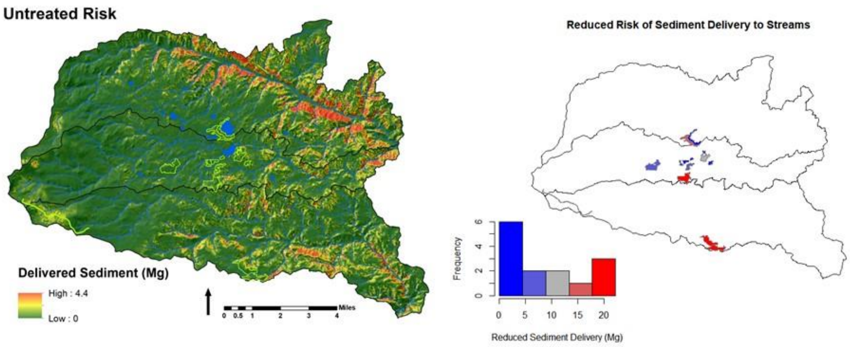
Risk of wildfire-related sediment delivery to streams (Figure 30) is the product of hazard of sediment delivery (Figure 29) and the 25-year burn probability, and should be interpreted as the expected impact over the assessment period (Finney 2005; Scott et al. 2013). Wildfire risk is lower than hazard because the probability of experiencing fire is far less than 1.0, even over a 25-year period. The maximum pixel-level risk of sediment delivery to streams is only 4.4 Mg over 25 years. The major change is de-emphasis of the hazard mapped at higher elevations (Figure 29), because these areas have the lowest burn probabilities. Treatment unit 4, which

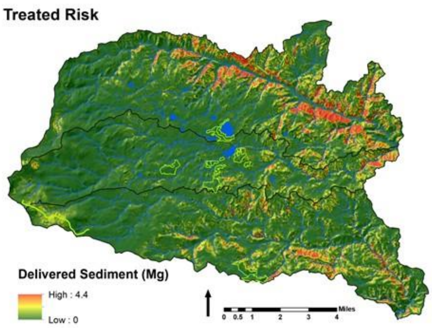




Hazard of Sediment Delivery to Streams (Mg)				
Treatment Unit	Pre-treatment	Post-treatment	Reduction	Percent Reduction
4	1159.3	603.1	556.2	48.0
13	372.2	144.9	227.3	61.1
2	279.3	104.2	175.1	62.7
12	294.6	126.6	168.0	57.0
5	159.6	48.7	110.9	69.5
1	169.1	62.0	107.2	63.4
6	167.7	68.8	98.9	59.0
3	100.5	39.8	60.8	60.5
14	63.1	31.9	31.2	49.5
8	42.0	14.3	27.8	66.0
7	38.0	14.4	23.6	62.1
11	18.2	6.7	11.5	63.1
10	19.1	7.8	11.3	59.2
9	5.0	1.7	3.2	65.1
		Total Reduction	1612.9	

Figure 29. Hazard of sediment delivered to streams (Mg) for pre- and post-treatment landscapes with application of the 14 mechanical only treatments. Hazard does not account for probability. The values should be interpreted as the mass of sediment delivered to streams if a pixel burns under 97th percentile conditions. The pre-treatment mass of sediment delivered to streams (UPPER LEFT) can be contrasted with the post-treatment mass of sediment delivered to streams (LOWER LEFT). To highlight the effect of treatment, the total reduction in mass of sediment delivered to streams was calculated for each treatment unit (UPPER RIGHT and LOWER RIGHT).





Risk of Sediment Delivery to Streams (Mg)				
Treatment Unit	Pre-treatment	Post-treatment	Reduction	Percent Reduction
13	35.6	13.5	22.2	62.2
2	31.1	11.7	19.4	62.4
12	32.7	14.0	18.7	57.2
5	19.4	5.9	13.5	69.6
4	25.7	12.8	12.8	50.1
6	19.4	8.1	11.3	58.3
1	12.2	4.5	7.7	62.9
3	12.0	4.8	7.3	60.4
14	6.7	3.2	3.4	51.8
7	4.2	1.6	2.6	61.1
8	3.4	1.2	2.2	64.6
11	2.6	1.0	1.7	63.2
10	2.0	0.8	1.2	59.1
9	0.3	0.1	0.2	66.8
		Total Reduction	124.1	

Figure 30. Risk of sediment delivered to streams (Mg) for pre- and post-treatment landscapes with application of the 14 mechanical only treatments. Risk accounts for probability of fire over a 25-year planning period. The values should be interpreted as the expected mass of sediment delivered to streams over the planning period, assuming all fires burn under 97th percentile conditions. The pre-treatment expected mass of sediment delivered to streams (UPPER LEFT) can be contrasted with the post-treatment expected mass of sediment delivered to streams (LOWER LEFT). To highlight the effect of treatment, the total reduction in expected mass of sediment delivered to streams was calculated for each treatment unit (UPPER RIGHT and LOWER RIGHT).

ranked as the highest value treatment by erosion hazard (Figure 27) and hazard of sediment delivery to streams (Figure 29), is now usurped by mid-elevation fuel reduction treatments. Estimated risk reductions vary from 0.2–22.2 Mg of sediment over 25 years for the 14 fuel reduction treatments, with a total estimated risk reduction from the body of work of 124.1 Mg of sediment delivered to streams.

5.4 Discussion

In the ARP proposed monitoring plan, watershed condition (Question 1), riparian, aquatic, and wetland condition (Question 5), and soil productivity and hydrologic function (Question 12), share some overlapping goals that relate broadly to the connected issues of soils and water. Wildfires and unpaved forest roads are the primary disturbances affecting soils in Colorado forests, followed by forest harvesting, the effects of which can often be controlled through best management practices (Macdonald and Stednick 2003). This analysis focused on the effects of wildfires on erosion and sediment delivery to streams, given that hazardous fuel treatment is a common management activity on the ARP, often with the goal of improving watershed resilience to wildfire.

This linked model approach allows for great flexibility in the temporal and spatial scales of analysis, and focus on erosion versus sediment delivery to streams. The framework can further be extended with a channel sediment transport model to examine the effects on downstream municipal water infrastructure. This flexibility can facilitate an integrated monitoring approach that addresses several monitoring questions with consistent analysis, but it also highlights the importance of specifying the process(es) to monitor and the spatial and temporal scales. Total treatment effects and the relative ranking of treatment units vary based on metrics of erosion hazard (Figure 27), hazard of sediment delivery to streams (Figure 29) and risk of sediment delivery to streams (Figure 30).

5.4.1 Erosion versus sediment delivery

Erosion rate is a reasonable metric to assess changes in soil productivity. Although the 14 fuel reduction treatments we examined were not located in areas of high erosion hazard, we estimate that they should reduce erosion 47.5-69.0% if the treated areas burn (Figure 27). The absolute magnitude of change in erosion rate depends on the baseline hazard, so prioritizing fuel reduction treatments in places with higher erosion hazard will yield larger reductions within the treated areas and the landscape as a whole. No assessment was made of the total landscape impact because we only examined the effects of a subset of existing activities, which cover a small percentage of the study landscape (1.3%). Since the monitoring goals relate to protecting the entire resources, a comparison of the total landscape baseline hazard with the total landscape hazard with treatment is a logical next step that would facilitate more quantitative goals, like reduce erosion hazard by 20%, rather than less quantitative metrics like improve watershed condition class. We did not present an erosion risk metric, but discussion will follow about the relative merits of using hazard and risk metrics.

It is well known that erosion does not equal downstream sediment delivery (Walling 1983). Although soil productivity and hydrologic function are lumped together in the same monitoring question (Question 12), their differences can lead to different prioritizations and assessments of fuel treatment work (e.g., the spatial differences in hazard between Figure 27 and Figure

29). Goals and indicators should be specific to the process and make it clear if there is a priority to avoid confusion about which indicator speaks to which goal.

5.4.2 Hazard versus risk

Language in the ARP proposed monitoring plan favors risk over hazard, consistent with assessment methodologies being promoted by the agency (Scott et al. 2013). An early critique of hazardous fuel treatment work focused on the relatively low probability of fuel treatments encountering wildfire (Rhodes and Baker 2008), and a recent observational study of wildfire-fuel treatment interactions found that only 6.8% of fuel treatment units encountered wildfire over a 13-year period (Barnett et al. 2016). As a minimum requirement, fuel treatments must encounter wildfire during their period of effectiveness to change fire behavior and reduce severity. The wildfire risk assessment framework (Scott et al. 2013), as well as any modern definition of wildfire risk, includes a likelihood component, usually by integrating a burn probability modeling product.

Burn probability modeling can help to prioritize placement of fuel treatments where they are more likely to function, i.e. encounter wildfire. It is important to recognize limitations with the approach to frame realistic objectives. Burn probability modeling involves simulating many thousands of wildfire events in a static fuelscape (fire 1 does not modify the fuel conditions for fire 2) with specified ignition patterns and fire weather conditions. Burn probability products are smooth (Figure 23) because of the high number of simulated events, which leads to a rather intuitive interpretation that, all other things being equal, fuel treatments will have higher risk reduction at lower elevation. Using burn probability modeling to prioritize or assess fuel treatment work should lead to higher long-term encounter rates and effects, but there is no guarantee that fuel treatment placed in the highest probability pixels will encounter a wildfire in the short-term (~25 years), given the high spatial and temporal variability of wildfire. It is important to acknowledge this uncertainty when presenting modeling results and to couple modeling with reporting of actual encounter rates. It is also important to update risk modeling components as fuel treatment work and other disturbances modify the fuelscape.

Hazard will overestimate the expected fuel treatment effects because it does not factor in the probability of fire, but it still has value. If monitoring questions relate to the magnitude of event-level impacts, hazard can be used to ask "what if this burns" questions at a variety of scales using zonal statistics in ArcGIS or similar tools. A more sophisticated version of this is to combine hazard metrics with many simulated fire boundaries to estimate the distribution of event-level effects (similar to Thompson et al. 2016). At a minimum, hazard metrics can be communicated along with risk metrics to convey the maximum estimated effects (hazard) along with the expected effects (risk).

5.5 Conclusions

There is a growing library of analytical tools that can help quantify the effects of fuel treatments on soil and water resources, that could help address monitoring questions 1, 5, and 12. The framework is adaptable to assess a variety of hazard and risk metrics related to local erosion, sediment delivery to streams, and with expansion, sediment delivery to downstream municipal infrastructure.

6 ENHANCEMENT OF WILDLIFE HABITAT

CFRI is currently working with the ARP to explore the extent to which monitoring methods and strategies previously developed by the Wildlife Working Team (WWT), a working group within the Front Range Collaborative Forest Restoration Program (FR-CFLRP), may be applicable to monitoring with the ARP forest plan. In this report, we aim to summarize the approach for selection of species by the WWT and describe the sampling design and monitoring approach used to monitor wildlife on FR-CFLRP projects. We also describe an additional study, conducted on FR-CFLRP projects, used to monitor wildlife sign before and after CFLRP restoration treatments (Briggs et al., 2017). By summarizing efforts currently being implemented through the CFLRP, we hope to inform the ARP on potential applications, shortcomings, and suggestions for wildlife monitoring program within the ARP as it relates to Forest Plan monitoring.

Developing a robust monitoring plan for wildlife on FR-CFLRP projects has been a complex process involving numerous experts and several phases of work. The original CFLRP monitoring plan (Clement and Brown 2011) contained suggestions regarding the most informative species and taxa to monitor, and recommended an initial focus on recording wildlife sign on Common Stand Exam plots before and after treatment. However, neither funding nor consensus on the desired conditions for wildlife were readily available for a full wildlife monitoring effort during the early years of CLFR work. Thus, the Landscape Restoration Team (a sub-team of the Front Range Roundtable) convened a group of wildlife experts in 2013 to develop a strong and functional monitoring plan moving forward. In the years that followed, this WWT worked through a process of selecting informative species to monitor, established monitoring options and protocols, and provided a path forward for wildlife

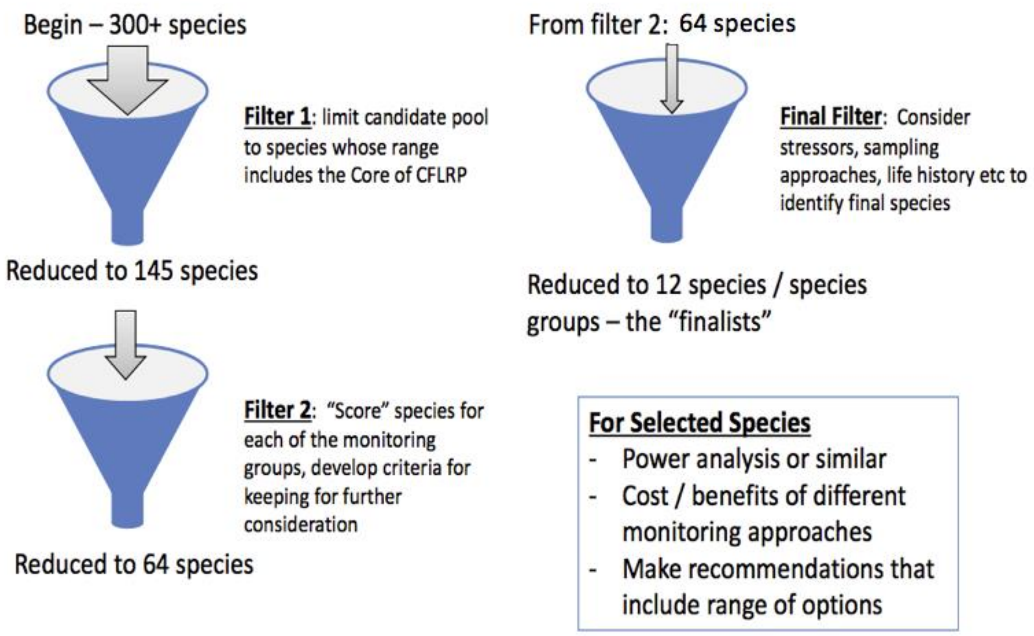


Figure 31. Schematic used by the Wildlife Working Team to describe the filtering process used to select species to monitor on Front Range CFLR projects.

monitoring on FR-CFLRP projects. This document is intended to describe that process, such that it can be repeated by other groups or agencies such as the ARP, as a wildlife-monitoring framework.

6.1 Filtering process

The initial step in selecting wildlife species to monitor by the WWT involved creating a comprehensive list of vertebrate species and invertebrate family/genera/species that occur in Front Range lower montane forests. This list was compiled using existing information such as the Colorado Natural Heritage Program database, field guides, local expertise, and agency "watch lists" (e.g. USFS Management Indicator Species, Threatened and Endangered Species, Candidate Species, etc.). This list of 302 species was then refined through a series of filters to create a more narrow, manageable suite of species upon which to focus monitoring efforts (Figure 31).

6.1.1 Filter 1: Distribution filter

The initial filter was designed to assess the distribution of each species relative to the CFLRP footprint, defined as Front Range lower montane forests, from 6,000 to 10,000 feet (1,800 to 3000 meters) in elevation. Species distributions were classified as follows:

1. **Core species**: Species whose known or suspected distribution includes the majority of the "core" CFLRP footprint.
2. **Marginal species:** Species whose known or suspected distribution is in *a portion* of the CFLRP footprint.
3. **Outside/Extirpated species:** Species whose range falls outside the CFLRP footprint, including species that formerly occurred but are not known to currently occur within the footprint.

All species with a distribution rated either "marginal" or "outside/extirpated" were removed from further consideration, leaving 145 species to consider.

6.1.2 Filter 2: Ranking filter

The remaining species whose distribution includes the core CFLRP footprint were then ranked based on how ecologically informative they are, their political prudence, and socio-economic importance. Species received a rank of 0-3 based on the following criteria:

1. **Ecologically informative:** Species were ranked on their key ecological functions (*sensu* Marcot and Heyden 2001) specialization, and reliance on lower montane forests to meet life cycle requirements. Although there was not a specific formula used to score species based on these sub-criteria, general guidelines were used to help inform scores.
   a. *Ecological Functions*: Species generally scored higher if they held higher trophic positions, represented strong organismal relationships (*e.g.*, pollinators, burrowing mammals, cavity excavators), and/or had a strong relationship with vegetation composition and structure (*e.g.*, heavy browsers).
   b. *Habitat Specialization*: Habitat specialists generally scored higher than generalists.
   c. *Reliance on lower montane*: species with a strong reliance on specific habitat components or successional stages within the lower montane forests scored higher. Residents generally scored higher than migrants.

2. **Political prudence:** Species received a score of 0-3 based on any political pressures that may be in place for conservation. A species received a score of 0 if it did not appear on any special status lists. A score of 1 was given if it appeared on a special status list such as state endangered, threatened, or special concern lists. A species received a score of 2 if it was a USFS Sensitive Species or Management Indicator Species, if it appeared on more than one special status list, or if it was a candidate species under the Endangered Species Act (ESA). A species received a score of 3 if it was listed as Threatened/Endangered or was proposed for listing under the ESA.

3. **Socio-economic importance:** Similar to the Ecologically Informative category, there was not a formula used to score the socio-economic importance of a species, but general guidelines were used. This category was designed to give some weight to species that are important to the public, such as game species (especially ones that generate substantial revenue for the State), watchable wildlife species, iconic species (such as the bald eagle or mountain bluebird), species that invoke high public interest (such as mountain pine beetle), or species of cultural significance.

After species received a score for each of the 3 described categories, each of the categories was summed up for a total score. Species remained under consideration if they received a total score greater than or equal to 3 AND an Ecologically Informative score greater than or equal to 1 OR any species with an Ecologically Informative Score greater than or equal to 2. This resulted in 64 remaining species.

6.1.3 Filter 3: Species consideration filter

The final step in the filtering process involved consideration of stressors, sampling logistics, and life history traits to generate a final list of priority species for monitoring. This stage of the filtering process involved group discussion to consider each of the remaining species. When evaluating a species for stressors, the group considered if changes in populations would be attributable to forest management practices, or some other stressor such as climate change or recreation. Consideration for sampling logistics included (1) whether sampling protocols exist and if data is already being collected for a given species, (2) difficulty or cost for monitoring, and (3) whether the species is detectable enough to be effectively monitored. Evaluating life history traits considered how informative a given species response to management actions may be given the goals of the CFLRP. For example, the Cooper’s hawk would not be considered as informative as the Northern goshawk due to its status as a generalist among all woodland habitats rather than a lower montane specialist. This final filter resulted in 12 remaining species/guilds, which the WWT further classified into Tier I and Tier II species (Table 13). Tier I species are top priority species for monitoring, while Tier II species represent species that are informative, but monitoring techniques are either not well established or sampling would be difficult at the scale of the CFLRP. Given the difficulties in monitoring Tier II species, the WWT recommended that those species be monitored opportunistically.

Table 13. FR-CFLRP wildlife working group recommendation of wildlife species to monitor.

Wildlife Guild/ Species	Tier I	Tier II	Sampling Methodology	Sampling Protocol	Metric
Bats: big brown bat, hoary bat, little brown bat, long-legged myotis, silver-haired bat, western long-eared myotis and western small-footed myotis.		X	Acoustic		Occupancy (% occupied)
Songbirds: golden-crowned kinglet, olive-sided flycatcher, mountain blue bird, and pygmy nuthatch.	X		Visual and Acoustic	Integrated Monitoring in Bird Conservation Region (IMBCR)	Occupancy (% occupied) and density (# of birds)
Woodpeckers: hairy woodpecker, and Williamson's sapsucker.	X		Visual and Acoustic	Integrated Monitoring of Bird Conservation Region (IMBCR)	Occupancy (% occupied) and density (# of birds)
Owls: flammulated owl		X	Visual and Acoustic	Partners in Flight Flammulated Owl Survey Protocol	Occupancy (% occupied)
Raptor: northern goshawk* * Note: the CFLRP has not monitored northern goshawk to date.	X		Visual and Acoustic	Northern Goshawk Inventory and Monitoring Technical Guide GTR WO-71	Occupancy (% occupied)
Tree Squirrels: pine squirrel and Abert's squirrel.	X		Wildlife Sign or Camera Trap	Sign surveys or Camera Traps	Occupancy (% occupied)
Carabid beetles: not species specific		X	Capture	Pitfall traps	Occupancy (% occupied) and density (# of invertebrates)

6.2 Sampling design

Monitoring for most Tier I species is conducted following established protocols for Integrated Monitoring in Bird Conservation Regions (IMBCR; White et al. 2016) in which point count surveys are located in 1 km^2 grids located throughout the Front Range (see Table 13 for sampling methods and protocols). Specifically, the FR-CFLRP uses a spatially balanced sampling design in which 120 grids are evenly distributed across Front Range National Forests (60 grids on the Pike-San Isabel (PSI), and 60 on the ARP; Figure 32). Of the 60 grids on each National Forest, 30 represent treatment grids, and 30 represent control grids. Treatment grids are defined as having greater than or equal to 30% (74.1 acres) of the grid receiving forest treatment. Additionally, sampling grids had to have at least 80% USFS ownership, fall within specific elevational bands (6000 – 9000 feet on the ARP, 6000 – 9500 feet on the PSI), have not burned in wildfires between 1998 and 2013, and could not fall outside the FR-CFLRP project boundary. Given these constraints, grids were randomly selected across both National Forests (Figure 32).

6.3 Monitoring protocol

Monitoring protocols utilized by the FR-CFLRP are intended to yield, at minimum, occupancy estimates for each species in treated and non-treated sites using presence/absence data (See Figure 33). In some cases, density estimates may also be calculated. The majority of Tier I species are sampled biennially on monitoring grids by the Bird Conservancy of the Rockies (BCR). Monitoring grids consist of 16 points, spaced 250 meters apart (Figure 33). Technicians

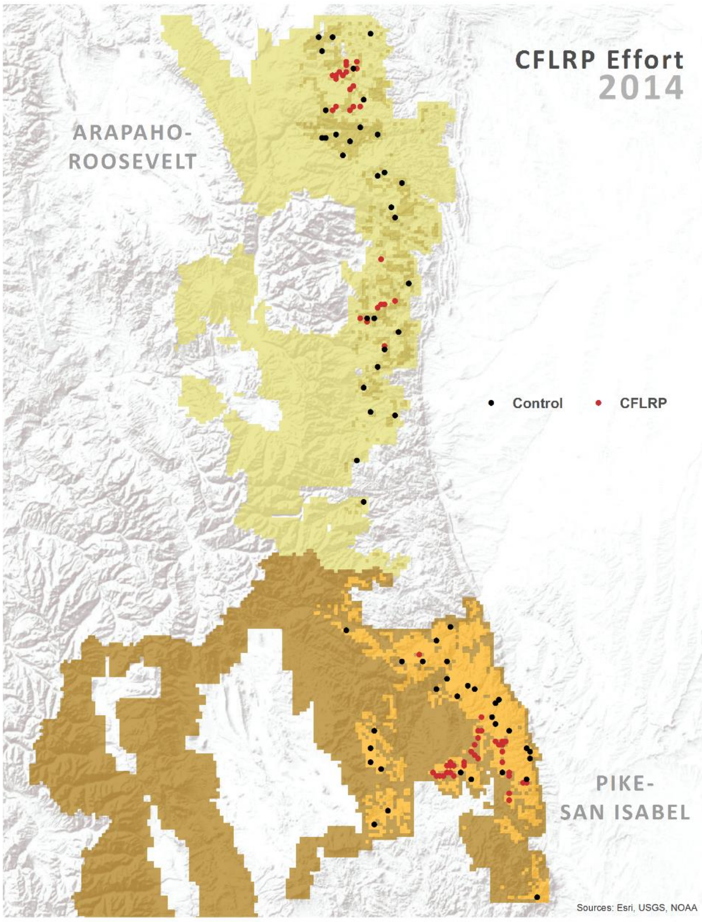
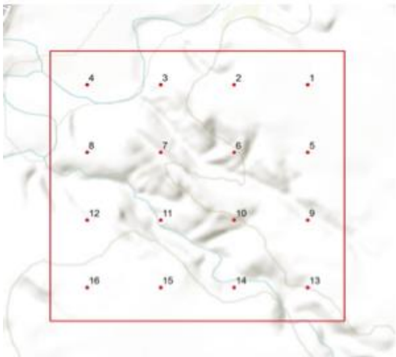


Figure 33. FR-CFLR wildlife monitoring grid locations. Image courtesy Casey Cooley, Colorado Parks & Wildlife.



	Pike-San Isabel Control				Arapaho-Roosevelt Control				CFLRP Treatments			
Species	Surveys	Psi	SE	% CV	Surveys	Psi	SE	% CV	Surveys	Psi	SE	% CV
Golden-crowned Kinglet	2	0.086	0.059	69	1	0.045	0.044	98	3	0.063	0.035	56
Olive-sided Flycatcher	2	0.091	0.062	68	2	0.094	0.064	68	7	0.151	0.054	36
Pygmy Nuthatch	13	0.525	0.11	21	10	0.41	0.106	26	33	0.636	0.076	12
Mountain Bluebird	6	0.248	0.091	37	6	0.256	0.094	37	8	0.159	0.053	33
Williamson's Sapsucker	8	0.42	0.131	31	2	0.112	0.077	69	18	0.452	0.096	21
Hairy Woodpecker	12	0.546	0.122	22	12	0.577	0.129	22	37	0.8	0.082	10
Red Squirrel	16	0.535	0.091	17	18	0.609	0.091	15	41	0.685	0.06	9

Figure 32. Left: Grid design used to monitor wildlife species for the FR-CFLRP. Right: Example of species occupancy data obtained from BCR monitoring effort. Image courtesy Casey Cooley, Colorado Parks and Wildlife.

sample grids consistent with protocols established by the Integrated Monitoring in Bird Conservation Regions (IMBCR) project (for full protocol see Hanni et al. 2016; White et al. 2016).

Technicians conduct surveys in the morning, beginning 30 minutes before sunrise, and concluding no later than 5 hours after sunrise. Points are sampled for 6 minutes, and technicians record the following attributes for each individual: species, sex, horizontal distance from observer, minute (referring to 6-minute sampling window), type of detection (visual, call, song), whether the individual is thought to be a migrant, and whether the observer is able to visually identify the individual. If individuals cannot be detected independently (e.g. flocks of conspecific birds), detections are recorded as a cluster, with the number of individuals included in the cluster rather than independent observations. Individuals that are not observed during a point count are also recorded opportunistically if they are observed while a technician is travelling between points. Opportunistic observations are used for mapping species distributions only, and are not used in any density or occupancy analyses. In addition to wildlife observations, technicians record weather measurements (temperature, wind, precipitation, and cloud cover) and coarse vegetation measurements within a 50-meter radius of the point. Vegetation measurements include dominant habitat type and relative abundances, percent cover and average height of trees and shrubs by species, grass height, and ground cover types.

In addition to the primary monitoring program described above, several species-specific monitoring approaches are also used. Because the IMBCR protocols rely on aural detections for species such as songbirds, woodpeckers, and the pine squirrel, they may not be effective in detecting less vocal species such as the Abert's squirrel. In an effort to more effectively monitor Abert's squirrel, the WWT initiated a pilot study with the USFS and Colorado Parks and Wildlife utilizing camera traps and feeding sign surveys at a subset of 40 IMBCR monitoring grids. In each of the 40 grids, one camera trap was deployed using peanut butter and a rabbit lure as attractant. These methods allowed for opportunistic detections of numerous species, as well as Abert's squirrel (Figure 34).

In addition to the camera trap, Abert's feeding sign transects were implemented at the center 4 points of each grid (Figure 33, points 6, 7, 10, and 11). At each of the sample points, 4 transects were sampled for signs of Abert's squirrel feeding activity (e.g. clippings and "cone cobs"). Results from the pilot study are pending, but preliminary results are promising as methods successfully detected Abert's squirrels yielding occupancy estimates. Additionally, since the USFS already regularly monitors goshawk on 5-year intervals using broadcast acoustical surveys, the FR-CFLRP leverages this data for goshawk occupancy estimation (see Woodbridge and Hargis 2006 for full protocol).

Currently, discussions are ongoing for analyzing data collected by BCR. The WWT is working with BCR to develop a list of habitat covariates from bird monitoring data. These covariates will help the group glean information on potential population changes based on several habitat metrics, sensitive to forest management, that are more easily monitored across the landscape.

6.4 Future directions

This report describes the framework used by WWT to select wildlife species to monitor for the FR-CFLRP. Although this approach is specific to lower montane forests along the Front Range, this framework can be applied to other ecosystem types. Given a comprehensive species list, and a working group of local experts, the process of filtering species by distribution, relevant criteria/values, and stressors/sampling logistics can be accomplished for other systems. The monitoring protocols described in this report outline methods that provide occupancy information for targeted species (e.g. IMBCR point counts), as well as opportunistic detections

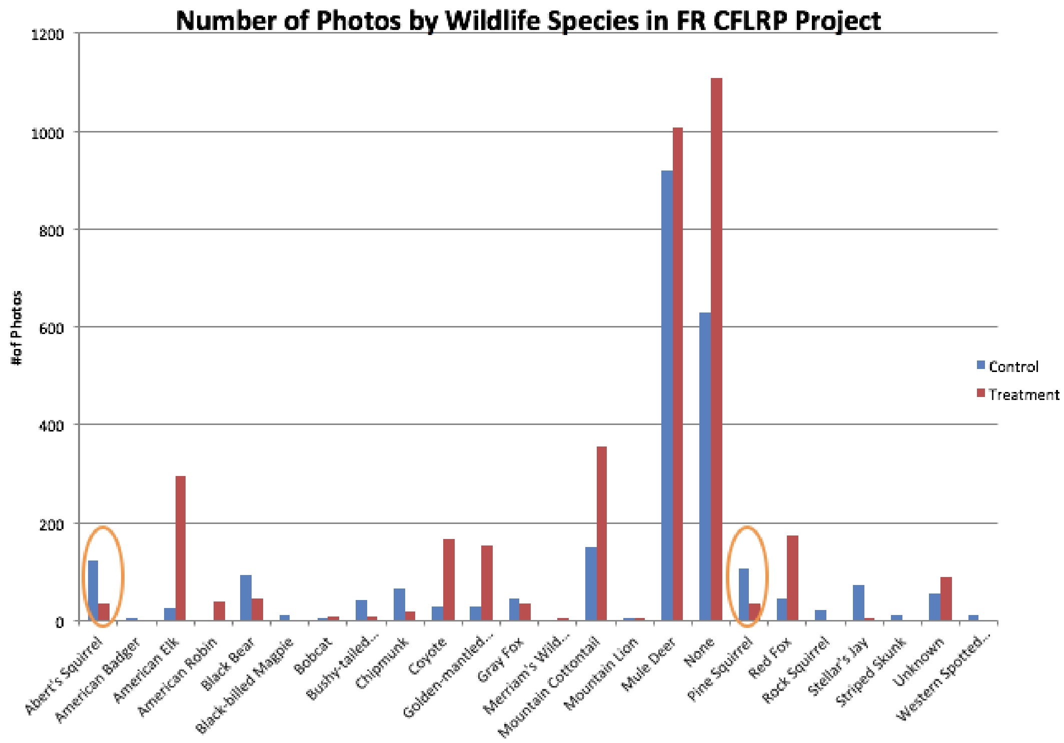


Figure 34.Wildlife detection data obtained from camera trapping effort, showing detections of tree squirrels, as well as numerous other opportunistic detections of other species. Image courtesy Casey Cooley, Colorado Parks and Wildlife.

of other species (*e.g.*, camera trapping), using a spatially balanced design to distribute sampling points among strata of interest. Results from this effort could be useful to the ARP, yielding habitat covariates associated with species occupancy and density estimates that may be more feasible to monitor than individual wildlife species.

While the process described above is one example of a tool used to select species for monitoring, other approaches could be utilized such as a correlation matrix of species occurrences. Given information on species detections at discrete locations, a correlation matrix could be utilized to determine which species commonly co-occur on the landscape. With this knowledge, land managers can selectively monitor fewer species, while inferring information on the larger community, thus saving time and money. Although the correlation matrix approach is a relatively simple analytical exercise, existing data on species occurrence related to discrete points in space limits the utility of this approach. To the best of our knowledge, aside from goshawk surveys conducted by the USFS, this type of data is only collected by the BCR on the ARP. Additionally, since this data is only related to birds, it is not possible to relate bird occurrence data with other taxa such as mammals, reptiles/amphibians, or insects. Finally, data made publicly available by the BCR only provides summarized occupancies by strata, and obtaining raw point counts has been exceedingly difficult. Unless the required data to compare species occurrences becomes available, the correlation matrix approach may not be possible.

Finally, (Briggs et al. 2017) conducted a study in which 0.1 acre circular plots were searched for signs of tree dwelling squirrels and ungulates on FR-CFLRP projects, finding no significant differences of habitat use resulting from forest treatment. These methods provide an additional approach to wildlife monitoring that does not require the high level of technical expertise that is required by the IMBCR point counts. Although this study did not find statistical differences in habitat use for squirrels and ungulates resulting from forest management, these measurements were taken shortly after forests were treated, and the authors suggest longer term monitoring to fully understand abundances, behavior, and distributions following treatment. Nonetheless, monitoring signs of habitat use could provide a more practical approach to monitoring wildlife than bird point counts, which require a high level of expertise in both monitoring and data analyses, given that fresh signs of chosen wildlife species can be easily observed.

6.5 Members of FR-CFLRP Wildlife Working Team

CFRI would like to acknowledge and thank the members of the Wildlife Working Team for their contributions toward the development of the process outlined in this document:

- **Rick Truex** – USFS, Rocky Mountain Region
- **Jenny Briggs** - USGS
- **Casey Cooley** – Colorado Parks and Wildlife
- **Lynne Deibel** – Arapaho Roosevelt National Forest
- **Steve Germaine** - USGS
- **Hal Gibbs** - USFS
- **Felix Quesada** – USFS Pikes Peak Ranger District
- **Janelle Valladares** – Pike San Isabel National Forest
- **Terra Lenihan** – (former) facilitator, Beh Consulting

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