

Evaluating ecological resilience across wildfire suppression levels under climate and fuel treatment scenarios using landscape simulation modelling

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Abstract. Continued suppression of wildfires may allow more biomass to accumulate to foster even more intense fires. Enlightened fire management involves explicitly determining concurrent levels of suppression, wildland fire use (allowing some fires to burn) and fuel treatments to manage landscapes for ecological resilience. This study used the mechanistic landscape model FireBGCv2 to simulate ecological dynamics on three landscapes in the US northern Rocky Mountains to determine responses of seven management-oriented variables over a gradient of 10 fire suppression levels under two climate and four fuel treatment scenarios. We used a historical range and variation (HRV) time series of the seven variables individually and merged together as a Principal Components factor (PC1) to define the envelope that represents ecological resiliency and compared all simulations with the HRV base case. We found that under today's climates, using the PC1 factor, ecological resilience was maintained while suppressing 30–90% of wildfires depending on the landscape. We also found fuel treatments might allow higher suppression levels to occur and still maintain resilience. Other findings indicate that each landscape must be individually evaluated to determine the right mix of wildfires, wildland fire use and fuel treatments depending on the response variables used to evaluate resilience.

Additional keywords: ecological tipping points, FireBGCv2, spatial modelling, wildland fire use.

Received 3 July 2018, accepted 5 May 2019, published online 4 June 2019

Introduction

Wildfires are becoming major concerns across the western US because they have increased in frequency, intensity and size in many areas over the past 20 years (Running 2006; Westerling *et al.* 2006; Falk *et al.* 2011; Westerling 2016). Prior to European settlement, wildfires in many western US dry forests were common and often non-lethal surface fires or mixed-severity crown fires that caused little ecological change and were somewhat easy to control (Arno 1980; Swetnam and Baisan 1996; Frost 1998; Heyerdahl *et al.* 2001). However, successful US fire exclusion by aggressive fire suppression during initial attack over the last century has kept fire out of many fire-prone forests, resulting in excessive build-ups of wildland surface and canopy fuel, which have, in turn, increased the potential for extreme fire behaviour (Brown 1985; Ferry *et al.* 1995; Keane *et al.* 2008; Flannigan *et al.* 2009).

This suppression legacy has left US fire management at a crossroads. Fire suppression costs are rising (Calkin *et al.* 2005; Snider *et al.* 2006), and if the current level of fire suppression continues, even more biomass will accumulate to create conditions that will foster even more severe fire behaviour than both contemporary or historical wildfires (Van Wagtenonk 1985; Keane *et al.* 2002). And to make matters worse, climates in western North America over the next century are predicted to be hotter and drier, creating longer and more severe fire seasons (Flannigan *et al.* 2013; Abatzoglou and Williams 2016; Westerling 2016; Kitzberger *et al.* 2017). Increasing fuel loadings and warmer climates may mean firefighters will be asked to fight increasingly dangerous fires, putting them at even higher risks of injury and fatality (Withen 2015).

The solution to this fire management dilemma will be extremely complex because it must integrate comprehensive

pro-active fuel treatment tactics (e.g. prescribed fire, mechanical cuttings) with wildland fire use (controlled wildfires or letting some fires burn under prescribed conditions) and focused wildfire suppression into a more effective and ecologically viable fire management strategy (Zimmerman and Bunnell 1999). At one end of the suppression spectrum is letting all fires burn, which would be difficult if not impossible in many parts of the western US because of the diverse societal values at risk, such as people, homes, power lines and municipal watersheds. At the other end of the spectrum is the current situation where 92–98% of all wildfires are suppressed, which is rapidly becoming unsustainable and is facilitating the perpetuation of extremely hazardous landscapes (Schoennagel *et al.* 2017). Therefore, determining the optimum levels of suppression and fuel treatments that maintain ecologically resilient landscapes while protecting the public, which are often major goals in public land management (USDA and USDI 2014; US Forest Service (USFS) 2012), will be especially challenging. A first step towards developing an integrated, ecologically based fire management strategy may be to identify those critical thresholds of wildfire suppression efforts where fuels, vegetation and fire conditions fall outside the envelope that defines landscape resilience. Are there level(s) of fire suppression that create conditions where vegetation, fuels and fire dynamics are within the bounds of a resilient ecosystem, which is often when fire hazard is low?

In this paper, we use historical conditions as a reference for characterising and quantifying ecological resilience for land management (Keane *et al.* 2009; Seidl *et al.* 2016; Keane *et al.* 2018). The historical range and variation (HRV) of ecological conditions before European settlement in the US have been used extensively and successfully as references, benchmarks or targets by researchers and land managers over the last two decades (see Hessburg *et al.* 1999; Keane *et al.* 2007). The assumption behind HRV is that variations of historical characteristics represent the broad envelope of responses possible for a resilient ecosystem under natural perturbations of climate, competitive stress, disturbances and other stressors (Keane *et al.* 2018). The HRV concept recognises that landscapes and ecosystems are dynamic and highly variable, and that potential responses to changing conditions are consequently best represented by past ecological conditions (Veblen 2003). We feel that the degree of departure of contemporary or future conditions from the historical time series of variables that represent HRV can then be used as a resilience metric for evaluating ecosystems or landscapes to inform potential strategies and tactics (Morgan *et al.* 1994; Landres *et al.* 1999).

Recently, the use of HRV as a reference to guide future land management has been challenged, primarily because climate and other environmental conditions are changing so rapidly that the future may be significantly different than any analogue in the ecologically relevant past; therefore, maintaining HRV may be impractical if not irrelevant (Millar and Woolfenden 1999; Millar *et al.* 2007; Shive *et al.* 2014). Although HRV may reflect the range of conditions under which the current flora and fauna have evolved, no-analogue future climate regimes may make it difficult to manage landscapes within historical envelopes (Falk and Millar 2016). However, ecosystems often possess powerful stabilising legacies that may buffer the impacts of change, including topo-climatic refugia, genetic adaptations to

emerging conditions and unexpressed phenotypic variation (Johnstone *et al.* 2016). Regardless, we feel that HRV remains a valuable tool to frame resilience-based management evaluations (Alagona *et al.* 2012; Seidl *et al.* 2016).

Although many papers have been written on the concepts of ecological thresholds, tipping points and phase transitions, there are few papers detailing how to quantitatively identify meaningful ecological thresholds. Andersen *et al.* (2009) mention several methods that have been used to detect changes over time, including average standard deviates, principal component analysis (PCA), regression analysis and classical statistics. PCA and chronological clustering were used to detect comparable marine ecosystem regime shift patterns in 78 time series from the North and Wadden seas (Weijerman *et al.* 2005), whereas Carpenter and Brock (2006) used increasing standard deviations of response variables over time as a signal of impending shifts. Rodionov (2004) notes the performance of threshold detection methods drastically diminishes at the ends of the series and regime shifts are usually detected long after they actually occurred, and, similarly, Biggs *et al.* (2009) used a spectral density ratio indicator to detect potential shifts in fisheries over time and found that regime shifts often occurred when it was too late for management to do anything. In the present paper, we used a statistical method that is rarely used in ecological applications to detect when a threshold is reached – Shewhart quality control charts (ShewhartQCCs) (Shewhart 1931). The ShewhartQCC method establishes an upper and lower limit calculated as three standard deviations away from a baseline mean value, and if consecutive observations fell outside the three standard deviations, we concluded that the landscape moved outside HRV conditions and was likely to no longer be ecologically resilient, and therefore a resilience threshold was reached.

In the context of the present study, we define a ‘resilience threshold’ as the minimum or maximum level of fire suppression after which there are significant, and possibly irreversible, changes in ecosystem resilience using management-oriented variables that are compared with historical time series (i.e. HRV) (Keane *et al.* 2018). Obviously, any resilience threshold would depend on the many feedbacks and interactions that are governed by myriad environmental factors, primarily the top-down processes of climate and weather as they interact with the bottom-up processes of fuel, vegetation, topography and land management to influence the biophysical environment at local scales (Heyerdahl *et al.* 2007; Merschel *et al.* 2014). Therefore, it is likely that resilience thresholds will be different across disparate landscapes, ecosystems, management strategies and climates (Keane *et al.* 2015a). In this paper, we assume that a fire suppression level is equivalent to the proportion of fires extinguished during initial attack and not the effort used to put out large fires, and that any ‘controlled’ wildfire that is allowed to burn under prescribed conditions is considered wildland fire use.

Landscape simulation modelling is perhaps the only method available to generate the extensive data needed at the time and space scales relevant to fire management to detect those suppression levels that push landscapes outside resilience thresholds (Davis *et al.* 2007; Hastings and Wysham 2010; McKenzie *et al.* 2014; Keane *et al.* 2015b). Empirical approaches, such as substitution of space for time (i.e. spatial chronosequences) or controlled field or laboratory experiments often require too

much data, need inordinately large areas, demand too much temporal depth, and have great uncertainties across scales (Keane *et al.* 2015a). Computer modelling of alternative scenarios has been used to detect critical thresholds in glacial settings (Ditlevsen and Johnsen 2010), marine landscapes (Monaco and Helmuth 2011) and terrestrial ecosystems (Reyer *et al.* 2015). To detect thresholds, these studies constructed experimental designs where the range of a management action (in the current paper, suppression levels) was simulated under various scenarios that reflect those important factors that may influence ecological response, and subsequently, changes in resilience. Moreover, in the present project, simulation modelling was used to generate the HRV time series that served as the reference for resilience (Keane *et al.* 2015b, 2018) so that the reference was quantified using the same method that was used to simulate the other scenarios. It was critical that the model used have a mechanistic design so that important interactions across biological components could be simulated at the appropriate scales (Gustafson 2013; Keane *et al.* 2015b).

We used a complex landscape simulation experiment to detect possible resilience thresholds under a gradient of fire suppression levels and various climate and fuel treatment scenarios. Ten levels of fire suppression were simulated on three US northern Rocky Mountain landscapes using the FireBGCv2 model (Keane *et al.* 2011) for two climate scenarios (historical and future hot, dry) and four fuel treatment scenarios (no treatment, 0.04% of landscape treated per year, 0.08% per year, and treat all available land each year). Response variables representing vegetation, fuels and fire were produced as output for statistical analysis. We applied multivariate statistical methods on the simulated data to detect when response variables went outside the HRV reference conditions that defined resilience. We then summarised these threshold levels across climate and fuel treatment levels to develop a set of possible management targets for the three landscapes. These resilience thresholds of fire suppression effort should provide fire managers insight into how many wildfires can be initially attacked before there are major changes in the ecological characteristics of landscapes, and if fuel treatments can be used in place of wildfires to maintain resilience.

Methods

FireBGCv2 model

FireBGCv2 is a mechanistic, individual-tree, gap model that is implemented in a spatial domain (see Keane *et al.* 2011 for complete model documentation, assumptions, parameters and validation). The model was developed by integrating empirically derived deterministic functions with stochastically driven algorithms to approximate landscape and ecosystem behaviour across time and space (Keane *et al.* 1996, 2011). Physical and empirical functions are used to represent well-studied ecological processes, such as respiration and photosynthesis, while stochastic functions are used to represent ecological processes that are highly variable, understudied and difficult to quantify, such as fire ignition, tree mortality and snag fall. FireBGCv2 is a cumulative-effects model that is best used to study long-term landscape dynamics rather than as a prognostic model to project short-term future conditions.

FireBGCv2 simulates ecological processes across multiple spatiotemporal scales (Fig. 1). Wildland fire ignition and spread, along with cone crop production and seed dispersal, are spatially simulated at the landscape level at the end of each simulation year. Most of the FireBGCv2 fine-scale simulation occurs at the stand level where the flows of carbon, nitrogen and water are distributed across various terrestrial and atmospheric components within the model. Important ecological processes modelled at the stand level include litterfall, decomposition, snow dynamics, transpiration and evaporation. Many processes are simulated at a daily time step, including species phenology, litterfall and water flux. Tree growth, establishment and mortality are simulated at the individual tree level at annual time steps, while disturbance effects, such as fuel consumption, tree mortality and soil heating, are computed across all scales of space and time.

Several FireBGCv2 components are important in this study and warrant mention here. There is a comprehensive module that simulates a wide variety of management actions, including partial harvest, planting, wildland fire use and prescribed burning at the stand scale (Keane *et al.* 2011); this module was used to simulate fuel treatments in the present study. There are also detailed fire algorithms that simulate (1) ignition based on weather, fuels and topography; (2) spread based on vectors of wind and slope (Rothermel 1972); (3) effects based on fire intensity and soil heating (Reinhardt *et al.* 1997); and (4) wildfire management based on proportion of fires suppressed, an input parameter (Keane *et al.* 2011). In FireBGCv2, fire suppression level is simulated as the relative proportion of fires that are suppressed at initial attack. The executable FireBGCv2 program used for this project is available from <https://new.cloudvault.usda.gov/index.php/s/8MxdEeES2A65xMa> (verified 14 May 2019).

Study areas

The simulation of the complex interactions of climate, fire and vegetation dynamics over the entire US northern Rocky Mountains is computationally intractable using FireBGCv2 at this time. Instead, we simulated landscape dynamics on three large landscapes that we felt represented the wide range of climate, vegetation and fire regimes in the northern Rocky Mountains (Fig. 2):

- East Fork Bitterroot River (EFBR) on the Bitterroot National Forest, Montana, USA: a 168 000-ha dry mixed-conifer ecosystem with frequent (10–100-year fire return intervals) and low-severity fire regimes that formed ponderosa pine and Douglas-fir forests at the lowest elevations, lodgepole pine and subalpine fir forests at the moderate elevations, and whitebark pine forests at the highest elevations (Holsinger *et al.* 2014).
- Crown of the Continent (CROWN) comprising the McDonald and Saint Mary's drainages of US Glacier National Park: a 140 000 ha mesic mixed-conifer landscape with fire regimes of moderate frequencies (50–300-year fire return intervals) and mixed severities that created western hemlock and cedar forests at low elevations, lodgepole and subalpine fir at mid-elevations, and whitebark pine habitat at the highest elevations (Loehman *et al.* 2011b).

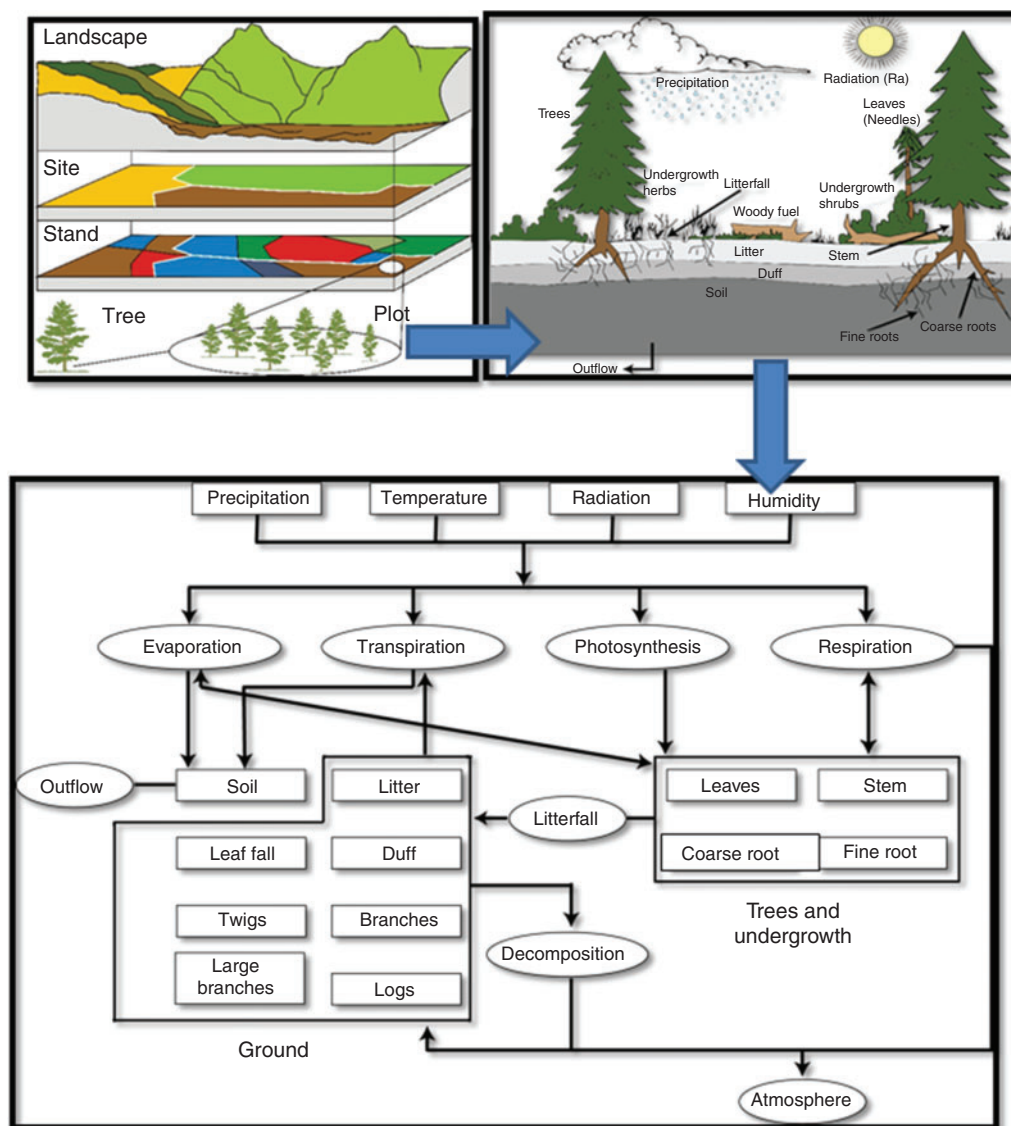


Fig. 1. A schematic of the FireBGCv2 model. The upper left shows the five scales represented by the model. Stand-level processes are simulated on a vignette of a stand called a plot. This plot comprises various ecosystem components (upper right panel), and the flow of energy, carbon, water and nitrogen is simulated across each of these components and important carbon pools (lower panel) using mechanistic algorithms detailed in [Keane *et al.* \(2011\)](#). The biophysical processes of evaporation, transpiration, photosynthesis and respiration are governed by five daily weather variables precipitation, maximum and minimum temperature, radiation and humidity.

- Yellowstone Central Plateau (YCP) in Yellowstone National Park: a 175 000-ha high-elevation (>2300 m) landscape in a volcanic caldera with mostly infrequent (>150-year fire return intervals), stand-replacement fire regimes composed mostly of mature lodgepole pine with scattered late-successional subalpine fir stands and whitebark pine stands in limited areas at the highest elevations ([Clark *et al.* 2017](#)).

We selected these three landscapes because we thought that they spanned the range of northern Rocky Mountain fire regimes ([Fig. 2](#); see [Agee 1993](#)). Because it takes over 1 year to parameterise, initialise and calibrate a FireBGCv2 landscape, we also selected these landscapes because they had been used in

previous FireBGCv2 studies: EFBR was parameterised by [Holsinger *et al.* \(2014\)](#), CROWN by [Loehman *et al.* \(2011b\)](#) and YCP by [Clark *et al.* \(2017\)](#).

Simulation experiment

We evaluated fire suppression thresholds in the context of three important factors that we thought would influence ecological resilience: climate, fuel treatments and landscape setting ([Table 1](#)). We used a fully factorial simulation design for this evaluation with four factors (fire suppression level, fuel treatment effort, climate and landscape) and each factor represented by several levels. The primary vector of evaluation for this

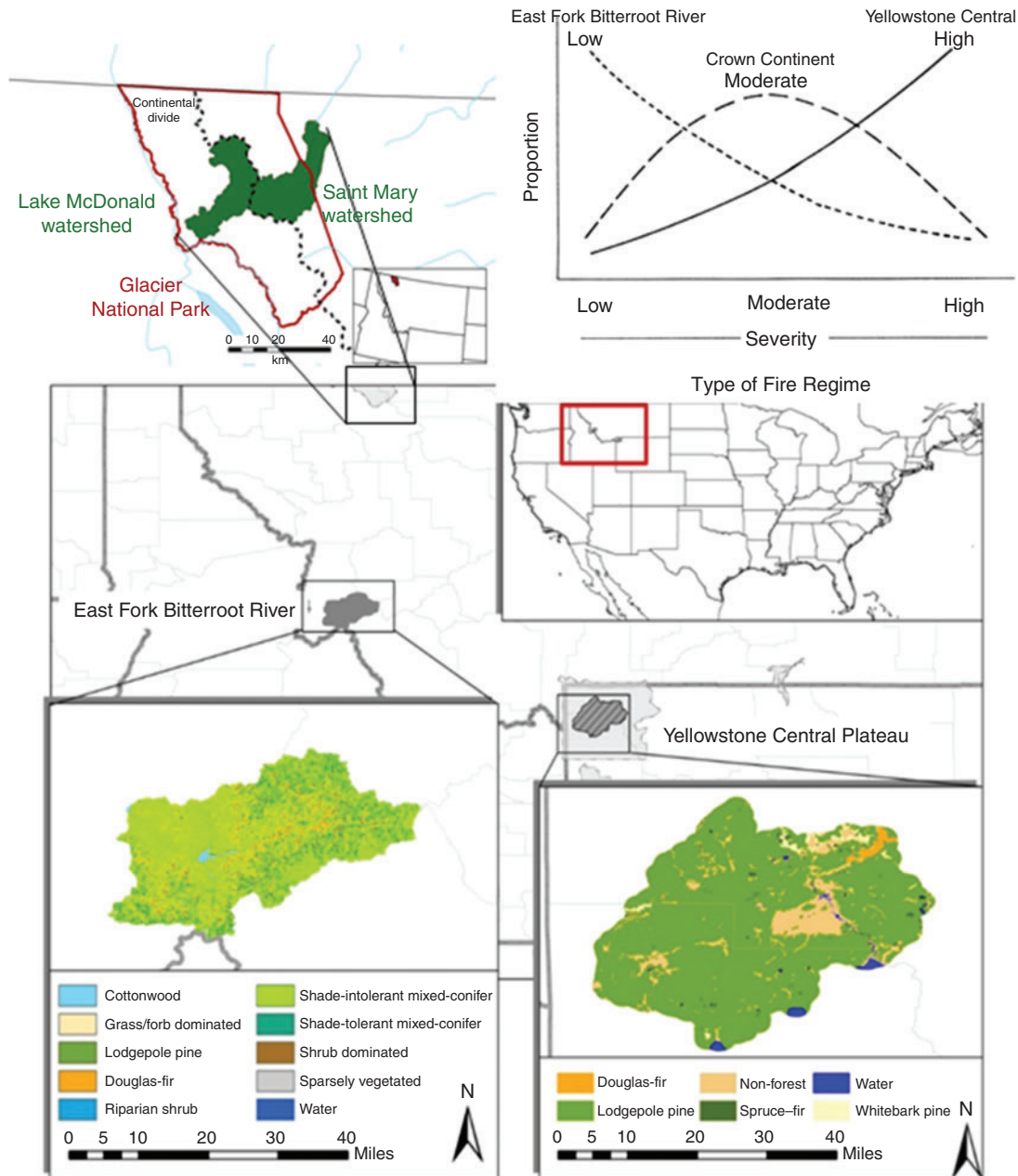


Fig. 2. The three US northern Rocky Mountain landscapes that were included in the FireBGCv2 simulations – EFBR, East Fork of the Bitterroot River; CROWN, Crown of the Continent, which includes Lake McDonald and Saint Mary watershed; and YCP, Yellowstone central plateau.

experiment was *fire suppression level* (FSL), where we simulated 10 levels of increasing fire suppression: 0% suppression (no fires suppressed; historical fire regime; proportion of fires suppressed is 0.0) to 90% suppression (estimated level of current fire suppression; proportion of fires suppressed is 0.9) by 10% increments (i.e. 0, 10, 20, 30... 90% suppression).

We then wanted to evaluate if resilience thresholds for FSL would be different if fuel treatments were also employed, so we simulated four levels of *fuel treatment effort* (FTE): (1) no treatments (N); (2) business as usual (BAU; 0.04% landscape

treated per year or ~ 6000 ha); (3) fully funded fuels program (FF; 0.08% landscape treated per year or 12 000 ha); and (4) no holds barred (NHB; treat all lands that need treatment annually). All fuel treatments were a combination of silvicultural cuttings to remove all fire-sensitive shade-tolerant species down to 4 cm diameter at breast height followed by a low-intensity prescribed burn (~ 400 kW m^{-1} fireline intensity) to reduce slash and kill understorey seedlings and saplings. FireBGCv2 only treats stands that are above a minimum basal area (10 m^2 ha^{-1}), contain fire-sensitive species (Table 1) and have high fuel

Table 1. The multifactorial simulation experiment used to assess possible thresholds in fire suppression effort along with details of the simulation (simulation specifications), and list of response variables used in the analysis $T_{\max}$, maximum daily temperature; $T_{\min}$, minimum daily temperature

Factor or variable	Levels, parameters, or units	Description
<i>Simulation design</i>		
Fire suppression level (FSL)	10	Proportion fires suppressed: 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 or 10, 20, 30, ... 90% suppression levels
Fuel treatment effort (FTE)	4	Mechanical thinning of fire sensitive species and subsequent prescribed burns at the following levels of implementation: none (N), 3% landscape treated (business as usual, BAU), 10% landscape treated (fully funded fuel treatment program, FF); treat all lands that need it (no holds barred, NHB)
Climate	2	Historical climate (HIST) and the hot, dry RCP8.5 scenario for the US northern Rocky Mountains (RCP8) where offsets were $T_{\max}$ 4.3, 5.5 and 6.8°C and $T_{\min}$ 4.8, 6.8, 6.8°C for EFBR, YCP, CROWN respectively, and precipitation increases were 200, 110 and 120% for the EFBR, YCP, and CROWN, respectively
Landscape	3	East Fork Bitterroot River (EFBR), Yellowstone Central Plateau (YCP) and Crown of Continent (CROWN) (Fig. 2)
<i>Simulation specifications</i>		
Simulation length	200 years	Simulated landscape dynamics for 200 years to get a full representation of the fire and fire management regimes
Simulation replications	10 replicates	Needed to get sufficient observations to detect thresholds but low enough number not to generate too many observations for statistics
Simulation output interval	10 years	Generated stand, site and landscape level output at decade intervals; used the last 100 years (10 observations) in the analysis
Time step	Daily	Cycled the 50+ year weather records for each landscape for 200 years
<i>Response variables</i>		
BA	$\text{m}^2 \text{ha}^{-1}$	Basal area of all trees across the landscape
CBD	kg m^{-3}	Canopy bulk density
CWD	kg m^{-2}	Coarse woody debris – downed woody material greater than 10-cm diameter
FWD	kg m^{-2}	Fine woody debris – downed woody material less than 10-cm diameter
TC	kg m^{-2}	Total carbon of living and dead biomass
PLFAS	%	Percentage of the landscape composed of fire-adapted species
PLBURN	%	Percentage of the landscape burned annually

loadings ($>5 \text{ kg m}^{-2}$). There were simulation years when there were few stands that met these criteria so sometimes treatment level targets were not reached (Keane *et al.* 2011).

We also wanted to assess if fire suppression thresholds were the same under future climates. The *climate* factor had two scenarios: a historical climate (HIST) and a future climate (RCP8) (Table 1). The historical climate was taken from a weather station that was within or near each simulation landscape (Keane *et al.* 2011); a 54-year daily observations record for the Sula, MT, weather station was used for EFBR simulations; a 55-year record from West Glacier, MT, was used for CROWN; and a 99-year record from West Yellowstone, MT, was used for YCP. Weather station data (maximum and minimum temperatures, precipitation, radiation and humidity) were extrapolated across each landscape using MTCLIM (Holsinger *et al.* 2014). The future climate data were created by adjusting historical climate variable values by offsets (Loehman *et al.* 2011b; Clark *et al.* 2017). We computed the offsets from data taken from the Coupled Model Intercomparison Project Phase 5 for the 8.5 Representative Concentration Pathway (RCP8) where average annual temperatures are projected at $\sim 6^\circ\text{C}$ above pre-industrial levels – an emissions scenario that predicts the highest temperature increases among various possible emission scenarios but the one that appears increasingly most likely to occur (Peters *et al.* 2013). Based on an evaluation of a suite of

Global Circulation Models by Rupp *et al.* (2013) for the Pacific Northwest and surrounding region, we chose the CNRM-CM5 model (National Centre of Meteorological Research, France), which was the highest-ranked model overall for the three landscapes (Rupp *et al.* 2013). Landscape daily weather input data were taken from a statistical downscaling of CNRM-CM5 modelled data using the Multivariate Adaptive Constructed Analogs (Abatzoglou and Brown 2012) method with the METDATA (Abatzoglou 2013) observational dataset as training data. The last factor (*landscape*) had three levels reflecting the three landscapes selected for simulation (EFBR, CROWN and YCP) (Fig. 2).

Each level for each of the four factors was simulated for 200 years in a multifactorial design with 10 replicates for a total of 2400 simulations for each landscape ($10 \text{ FSL} \times 4 \text{ FTE} \times 2 \text{ climate} \times 3 \text{ landscapes} \times 10 \text{ replicates} = 2400 \text{ runs}$). The HRV reference for each landscape was no fire suppression, no fuel treatments, and historical climates. The same tree species list was used for each simulation run (Keane *et al.* 2015a), which dictated which species that could inhabit or migrate into the landscape during simulations. We produced values for seven response variables (Table 1) every 10 years for 200 years to create a simulation time series of 20 observations for each simulation run. Although FireBGCv2 can produce values for over 3000 variables, we selected the seven response variables in

Table 1 because they are often important in land management and they are correlated with many other output variables (Keane *et al.* 2011). For simulations using historical climate, we continually repeated the 50+ year weather record for the full 200-year simulation, and for the future climate simulations, we also cycled the weather years but ramped the weather so the offsets were fully implemented after 100 years, and then kept the offsets constant for the remaining simulation time (Holsinger *et al.* 2014). All input FireBGCv2 input files are available at <https://new.cloudvault.usda.gov/index.php/s/8MxdEeES2A65xMa>.

Statistical analysis

We detected threshold departures from HRV conditions for the simulated seven output variables using a suite of statistical approaches in the *R* statistical package (R Core Team 2017). As mentioned, ShewhartQCC (Shewhart 1931) was used to determine the FSL at which response variables were statistically different from the baseline HRV simulation. An average HRV value for each variable was calculated to establish the baseline (centre value) and we used three standard deviations above and below this mean to define the resilience envelope. To eliminate effects of initial conditions and to avoid the pitfall of generating an overabundance of observations to detect statistically significant differences (White *et al.* 2014), we used only the years 100–200 (100 observations = 10 output intervals and 10 replicates) in all Shewhart QCC statistical analyses.

Recognising that resilience threshold detection might depend on the response variables evaluated, we used PCA on the seven response variables to reduce the dimensionality of the data and evaluate trends in fire suppression levels based on the entire suite of the seven variables. Only the first and second principal components (PC1, PC2) were evaluated in our PCA analysis. ShewhartQCC plots were created using PC1 values and the methods described above for individual variable were implemented to detect when resilience thresholds were reached.

We compared different treatment combinations with HRV by fitting a linear mixed-effect model that included the fixed effects of FTE, climate, FSL and simulation year (YEAR), as well as a random effect of simulation replicates that accounted for the repeated measures in the data. All two-way interactions were included in the model. A linear mixed-effect model was fitted for each response variable separately. The significance of each term was examined, and tables and plots were created to examine differences between each FSL–climate–FTE combination and HRV conditions. Regression coefficients were examined to determine the magnitude and significance of differences between HRV simulations and other treatment combinations.

Results

Univariate analysis

We created and evaluated a suite of ShewhartQCC charts for the seven response variables (Table 1) over the gradient of FSLs to detect threshold violations (Table 2; Fig. S1). Charts for only basal area (BA) are presented in Fig. 3 for simplicity and to provide examples; charts for the remaining variables can be found in the supplementary material (Fig. S1). For EFBR, the landscape did not move outside HRV BA conditions until ~80%

of fires were suppressed regardless of all but the NHB fuel treatment (Fig. 3); the NHB treatment appears to create a landscape that is well outside the BA HRV time series regardless of climate and FSL. Most of the RCP8 simulations had shifts from HRV at low fire suppression levels because of the increased fire (3.2 times more area burned) in the future; however, higher fire suppression levels (>80%) moved EFBR into HRV levels for some variables (Table 2, Fig. 3). For both climate scenarios, three FTE scenarios (N, BAU, FF) appeared to be most effective at high fire suppression levels (>80%); there were little differences between them at lower suppression levels (Table 2, Fig. 3).

Most response variables did not exceed an FSL resilience threshold for the CROWN simulations for the HIST climate (Table 2; Fig. S2); it appears that resilience thresholds would most likely occur above the 90% level (Fig. 3). When evaluating BA, it appears that any level of fuel treatment except for NHB will keep CROWN within HRV across all FSLs (Fig. 3), and, as with EFBR, the NHB created a CROWN landscape significantly different from HRV (Fig. 3). The RCP8 climate had ~3 times more fire that generally caused a significant movement away from HRV at the low fire suppression levels (0.0–0.3 proportion suppressed) but the landscape was within HRV for higher levels of suppression (Table 2). The exception was for the variable canopy bulk density (CBD), which was outside the bounds for the RCP8 simulations under 30% suppression (Table 2).

All YCP simulations stayed within HRV conditions across all FSLs for all FTE levels under the HIST climate (Table 2, Fig. 3; Fig. S3). It is interesting that the effects of NHB fuel treatments were quite different from the other FTEs across all FSLs on the YCP. RCP8 climates created YCP landscapes that experienced 2.6 more fire that created conditions that were entirely outside HRV regardless of FSL and FTE effects across all variables except coarse woody debris (CWD) (Table 2). Effects of fire suppression level were minimal for the YCP BA simulations and no thresholds crossed (Fig. 3).

Principal component analysis

As mentioned, PCA was used to condense all seven variables to one or two components for ease of evaluation. The first principal component (PC1) of the EFBR simulations explained 72.6% of the variation in the response variables while the second component (PC2) explained an additional 14.5% (Table 3). The PC1- and PC2-explained variation was 63.1 and 17.3% for CROWN respectively, and 83.6 and 7.8% for YCP (Table 3). Variables that were most correlated with PC1 for all landscapes were BA, CBD, CWD, fine woody debris (FWD) and total carbon (TC), indicating that PC1 is a gradient of live and dead biomass; PC2 was most correlated with the proportion of the landscape in fire-adapted species (PLFAS) or species composition (Table 3). Large negative PC1 scores represented simulations with high fuel loadings (high values of CWD, FWD, CBD) on the EFBR and YCP landscapes, but the opposite was found on CROWN where large positive scores represented simulations with higher FWD, CWD, CBD values (Fig. 4).

We found a negative trend in PC1 scores occurred as FSL increased for EFBR and YCP (fuels accumulated), whereas a positive trend occurred in CROWN for both climates

Table 2. The fire suppression level (FSL; proportion of fires suppressed, [Table 1](#)) thresholds for all seven response variables by the two climate (HIST, historical climate; RCP8, future climate under RCP8.5 scenario) and four fuel treatment efforts (FTE; N, no fuel treatments; BAU, business as usual or 0.04% of landscape treated per year; FF, fully funded program or 0.08% treated annually; and NHB, no holds barred) based on the Shewhart quality control chart (ShewhartQCC) analysis

If no threshold was detected, then 'None' is reported in the table. For cases in which the variables came back into the bounds, two numbers are given, the first in which the system first exhibited a shift and the second in which the system went back into historical range and variation (HRV). If three numbers are given, then system went back out of HRV

Factor Combination	Basal area, BA (m ² ha ⁻¹)	Canopy bulk density, CBD (kg m ⁻³)	Coarse woody debris, CWD (kg m ⁻²)	Fine woody debris, FWD (kg m ⁻²)	Total carbon, TC (kg m ⁻²)	Percent landscape fire species, PLFAS (%)	Percent landscape burned, PLBURN (%)
<i>East Fork of Bitterroot River (EFBR)</i>							
HIST/N	0.8	None	0.3	0.7	0.4	None	None
HIST/BAU	0.8	None	0.4	0.6	0.5	0.5	None
HIST/FF	0.8	None	0.4	0.6	0.5	0.2, 0.3, 0.8	None
HIST/NHB	0.0	0.0, 0.9	0.0, 0.9	0.0, 0.7	0.0, 0.9	0.0, 0.5	0.0, 0.7
RCP8/N	0.0	0.0	0.0, 0.8	0.0, 0.6	0.0	None	None
RCP8/BAU	0.0, 0.8	0.0, 0.7	0.0, 0.5, 0.8	None	0.0, 0.6	None	0.0, 0.4
RCP8/FF	0.0, 0.8	0.0, 0.6	0.0, 0.5, 0.8	None	0.0, 0.6	0.8	0.0, 0.5
RCP8/NHB	0.0	0.0, 0.9	0.0, 0.9	0, 0.4, 0.5, 0.7	0.0, 0.9	0.0, 0.5	0.0, 0.7
<i>Crown of Continent (CROWN)</i>							
HIST/N	0.8	0.5	None	None	None	None	None
HIST/BAU	None	0.5, 0.7	None	None	None	0.7	None
HIST/FF	None	None	None	None	None	None	None
HIST/NHB	0.0	0.0	None	0.0	None	0.0, 0.5	None
RCP8/N	0.0, 0.2	0.2	None	0.0, 0.2	0.0, 0.2	0.0, 0.6	None
RCP8/BAU	0.0, 0.2	0.1	None	0.0, 0.3	None	0.0, 0.5	None
RCP8/FF	0.0, 0.3	0.3	None	0.0, 0.3	0.0, 2	0.0, 0.6	None
RCP8/NHB	0.0	0.0	None	0.0	0.0, 0.6	0.0	None
<i>Yellowstone Central Plateau (YCP)</i>							
HIST/N	None	None	None	None	None	None	None
HIST/BAU	None	None	None	None	None	None	None
HIST/FF	None	None	None	None	None	None	None
HIST/NHB	None	None	None	None	None	None	None
RCP8/N	0.0	0.0	None	0.0, 0.8	0.0	0.0	0.0, 0.7
RCP8/BAU	0.0	0.0	None	0.0, 0.9	0.0	0.0	0.0, 0.8
RCP8/FF	0.0	0.0	None	0.0, 0.9	0.0	0.0	0.0, 0.8
RCP8/NHB	0.0	0.0	None	0.0	0.0	0.0	0.0, 0.8

(Fig. 4a, b, c). YCP had the largest difference in PC1 scores between HIST and RCP8 simulations (Fig. 4c). For all three landscapes, differences between HIST and RCP8 climates were less significant as FSL increased, implying that higher FSLs may mitigate effects of warming climates (Fig. 4). For example, PC1 scores for historical climates at zero suppression for CROWN were similar to scores for RCP8 climates at 90% suppression levels, indicating that managing resilience under RCP8 climates may need high fire suppression levels to mitigate the high burned area to mimic HRV conditions. For all three landscapes, differences between the lighter FTEs (N, BAU and FF) were small (Fig. 4d, e, f). Similar to results of the univariate analysis, the NHB fuel treatment scenario on the EFBR and CROWN landscapes had significantly different PC1 scores than all other FTE scenarios across all FSLs, whereas on the YCP landscape, the NHB simulations had only slightly larger PC1 scores than the other FTEs (Fig. 4d, e, f). At fire suppression levels of 0.0 to 0.3 (0 to 30%), the BAU, FF and N treatments were similar to HRV levels for EFBR and CROWN (Fig. 4d, e). For both EFBR and CROWN, the NHB fuel treatment was close

to HRV levels for a fire suppression level of 0.9, or 90% fire suppression (Fig. 4a, b, d, e). All fuel treatments on the YCP were similar to HRV levels across all FSLs (Fig. 4f).

Results of the ShewhartQCC analysis of PC1 and PC2 scores were similar to univariate results with some important exceptions (Table 3). The second principal component (PC2) accounted for such little variation in response variables for all three landscapes that none of the factor combinations differed significantly from the base value of HRV (Table 3). Based on only PC1 scores, it appears that the FSL threshold for EFBR was ~40%, but the other two landscapes did not display any clear threshold for the HIST climate across three FTE scenarios (N, BAU, FF). Also similarly to univariate analysis results, the NHB fuel treatment scenario created conditions that were outside HRV for all three landscapes and both climates (Fig. 5). For EFBR only, the RCP8 simulations were significantly different than HRV at FSLs between 0 and 70%, but high suppression levels moved EFBR into HRV (Table 3, Fig. 5). All of the HIST simulations for EFBR were considered statistically different than HRV at FSLs above 40% with the exception of NHB, which

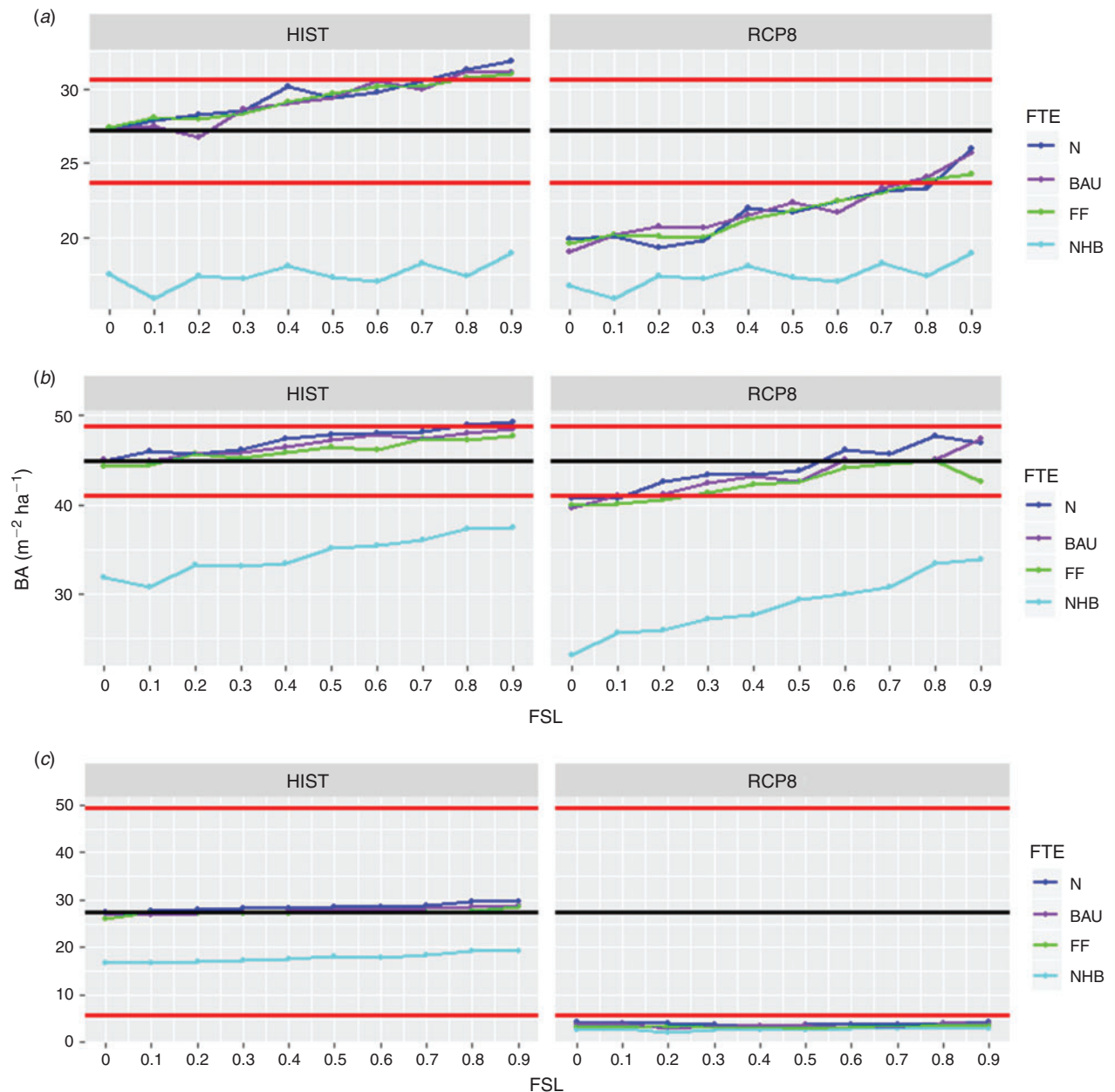


Fig. 3. Shewhart quality control charts (Shewhart QCCs) for the response variable basal area (BA; $\text{m}^2 \text{ha}^{-1}$) across the fire suppression levels (FSL; 0.1 means 10% fires suppressed) for the two climate scenarios (HIST, historical; RCP8, future climate under RCP8.5 scenario) and four fuel treatment effort (FTE) scenarios (BAU, business as usual, blue line; FF, fully funded, pink line; N, no treatments, green; and NHB, no holds barred, light blue) (Table 1) for all three study areas (a) EFBR, East Fork Bitterroot River; (b) CROWN, Crown of the Continent; and (c) YCP, Yellowstone (see Fig. 2 for locations). The black line represents the average BA ($\text{m}^2 \text{ha}^{-1}$) for historical range and variation (HRV) conditions and the red lines represent three standard deviations above or below this baseline value. QCCs for all response variables can be found in the Supplementary material Figs S1, S2 and S3.

was statistically different than HRV at an FSL of 0 (Table 3, Fig. 5). Although it appears that the CROWN landscape stayed within HRV under future climates (Fig. 5b), the YCP simulations showed all of the RCP8 simulations were significantly different than HRV (Table 3, Fig. 5). The CROWN simulations only deviated from HRV when the NHB treatment was implemented. These shifts were within three standard deviations of HRV at higher FSLs implying that HRV conditions could be met

at higher suppression levels with the NHB treatment (Table 3, Fig. 5).

Linear mixed-effects model

Most main effects and two-way interactions were highly significant for most of the seven variables in Table 1 for all three landscapes, indicating major statistically significant differences across all scenarios (Table 4; Figs S4–S6). Simulation year

Table 3. Summary statistics of the principal component analysis (PCA) for the first two axes (PC1, PC2) for all three landscapes (Table 1; Fig. 2) showing the standard deviation about the two axes, the proportion of the variance explained by the two components

Multivariate results of the Shewhart quality control chart (ShewhartQCC) analysis for the first two PCA axes for all three landscapes and for both climate scenarios (HIST, historical; RCP8, RCP8.5 scenario; Table 1) for the four fuel treatment scenarios (FTE; N, no fuel treatments; BAU, business as usual or 0.04% of landscape treated per year; FF, fully funded program or 0.08% treated annually; and NHB, no holds barred). Results shown are the fire suppression levels (FSL) at which the PC1 and PC2 values first exhibited a medium shift from the baseline conditions or historical range and variation (HRV). Additional numbers represent when the system went back into either the upper or lower bound. If a shift was not observed, then ‘None’ is reported in the table. EFBR, East Fork Bitterroot River; CROWN, Crown of the Continent; YCP, Yellowstone central plateau

Statistic	EFBR		CROWN		YCP	
Principal component	PC1	PC2	PC1	PC2	PC1	PC2
Standard deviation	2.227	0.987	2.14	1.17	2.419	0.741
Proportion variance	0.726	0.145	0.657	0.194	0.836	0.078
ShewhartQCC results for threshold fire suppression levels						
HIST/N	0.4	None	None	None	None	None
HIST/BAU	0.5	None	None	None	None	None
HIST/FF	0.4	None	None	None	None	None
HIST/NHB	0.0, 0.9	None	0.0, 0.4	None	None	None
RCP8/N	0.0, 0.6	None	None	None	0.0	None
RCP8/BAU	0.0, 0.5	None	None	None	0.0	None
RCP8/FF	0.0, 0.6	None	None	None	0.0	None
RCP8/NHB	0.0, 0.9	None	0.0, 0.8	None	0.0	None

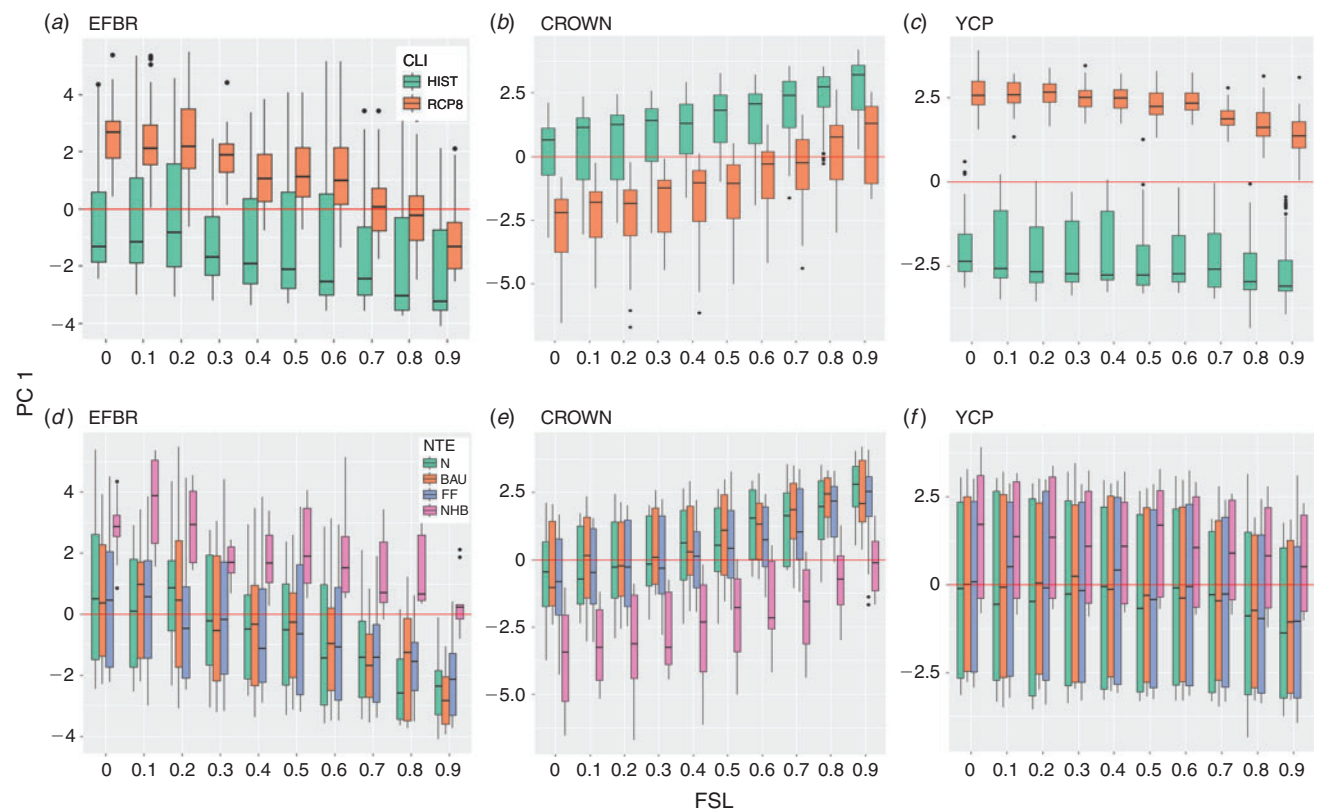


Fig. 4. Box-and-whisker plots showing the range in PC1 scores for the two climate scenarios (HIST, historical, green; and RCP8, RCP8.5, orange) across all fuel treatment effort (FTE) scenarios for the (a) EFBR, East Fork Bitterroot River; (b) CROWN, Crown of the Continent; and (c) YCP, Yellowstone central plateau landscapes (Fig. 2) and also for the four fuel treatment scenarios (BAU, business as usual, orange; FF, fully funded, blue; N, no treatments, green; and NHB, no holds barred, blue) (Table 1) across both climates for the (d) EFBR; (e) CROWN; and (f) YCP landscapes. The black line in the box indicates a median PC1 score, the box top and bottoms indicate the 25th and 75th percentile bounds, and outliers are represented by dots.

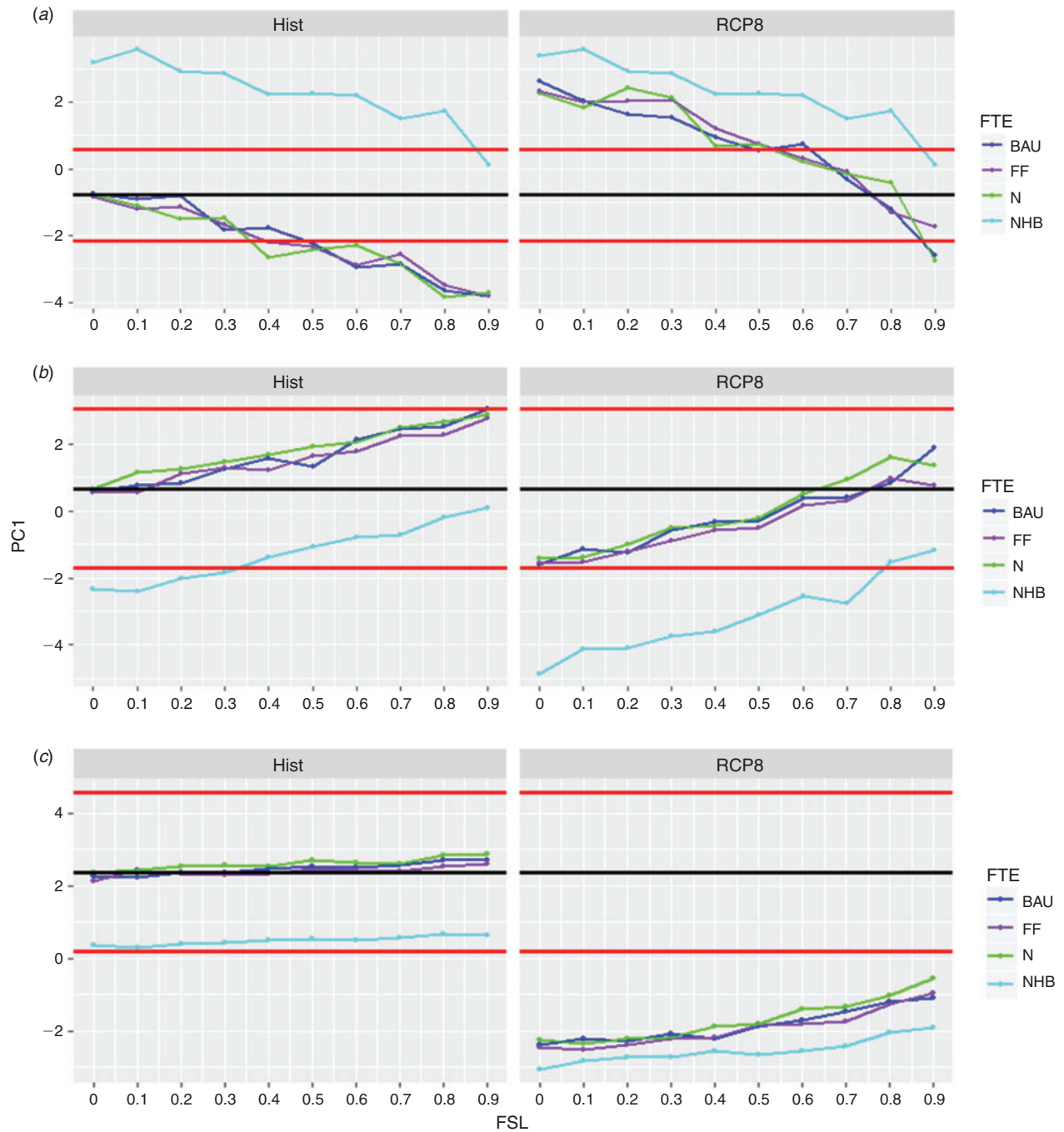


Fig. 5. Shewhart quality control charts (Shewhart QCCs) using the PC1 scores across the fire suppression levels (FSL; 0.1 indicates 10% fires suppressed) for the two climate scenarios (HIST, historical climate; RCP8, future climate under RCP8.5 scenario) (Table 1) across all three study areas (a) EFBR, East Fork Bitterroot River; (b) CROWN, Crown of the Continent; and (c) YCP, Yellowstone. The black line represents the average PC1 score for historical range and variation (HRV) conditions and the red lines represent three standard deviations above or below this baseline value. Colours of the lines represent fuel treatment effort (FTE) where BAU is business as usual (blue), FF is a fully functional program (purple), N is no treatments (green), and NHB is no holds barred (treat everything) (light blue) (Table 1).

(YEAR) was highly significant for all variables with the exception of CBD (P value 0.058) and FWD (P value 0.484) on the EFBR, percent landscape burned annually (PLBURN) (P value <0.387) on the CROWN, and TC (P value <0.223) for YCP, indicating significant changes in values across the

100-year simulation. The two-way interaction of FTE and climate was also highly significant for all the variables but PLFAS (P value 0.161) on EFBR, CWD and FWD on CROWN, and PLBURN on YCP (Table 4), implying that the effects of fuel treatment are different across climate scenarios. And last, the

Table 4. Results from of the linear mixed-effects model analysis that include fixed effects and all two-way interactions of fuel treatment effort (FTE), climate (CLI), fire suppression level (FSL) and simulation year (YEAR) as well as the random effects of simulation to account for repeated measures *P* values are reported for all three landscapes: the East Fork of the Bitterroot River (EFBR), the Crown of the Continent (CROWN), and the Yellowstone central plateau (YCP) (Fig. 2). The variables are basal area (BA), canopy bulk density (CBD), coarse woody debris (CWD), fine woody debris (FWD), total carbon (TC), percentage of the landscape in fire-adapted species (PLFAS), and percentage of the landscape burned each year (PLBURN) (see Table 1 for more details). DF is degrees of freedom. The *P* value is reported for each term for each response variable with numbers in bold indicating no statistical significance (*P* value < 0.05)

Term	DF	BA	CBD	CWD	FWD	TC	PLFAS	PLBURN
East Fork of Bitterroot River (EFBR)								
FSL	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
CLI	1	<0.001	<0.001	<0.001	<0.001	<0.001	0.0286	<0.001
FTE	3	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
YEAR	1	<0.001	0.0575	<0.001	0.476	<0.001	<0.001	<0.001
FTE*CLI	3	<0.001	<0.001	<0.001	<0.001	<0.001	0.161	<0.001
FTE*FSL	3	<0.001	0.0178	<0.001	<0.001	<0.001	<0.001	<0.001
FSL*CLI	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Crown of the Continent (CROWN)								
FSL	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
CLI	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
FTE	3	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
YEAR	1	0.018	<0.001	<0.001	<0.001	<0.001	<0.001	0.387
FTE*CLI	3	<0.001	<0.001	0.419	0.165	<0.001	<0.001	0.851
FTE*FSL	3	<0.001	<0.001	0.104	<0.001	<0.001	<0.001	0.082
FSL*CLI	1	<0.001	<0.001	0.032	<0.001	<0.001	<0.001	0.057
Yellowstone Central Plateau (YCP)								
FSL	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
CLI	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
FTE	3	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.232
YEAR	1	<0.001	<0.001	<0.001	<0.001	0.223	<0.001	<0.001
FTE*CLI	3	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.992
FTE*FSL	3	0.231	0.127	<0.001	0.004	<0.001	0.124	0.489
FSL*CLI	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

FTE and FSL interaction was significant for all variables except CWD and PLBURN on CROWN and CWD and PLBURN on YCP, indicating the effect of fire suppression levels are different across fuel treatments (Table 4).

In general, we found no significant differences between HRV and the three lightest FTE scenarios (N, BAU, FF) for the EFBR and CROWN landscapes using three important variables (BA, CBD, PLFAS) regardless of FSL (Fig. 6; Figs S4–S6). We also found that there were few differences in BA between HRV and BAU and FF for all three variables (Fig. 6; BA, CBD, and PLFAS) at zero fire suppression level, indicating the ineffectiveness of fuel treatments when fires are allowed to burn. Under future climates (RCP8), all FTE scenarios had less BA and CBD in the EFBR and YCP landscapes owing to increased fire, and there were more fire-adapted species on both landscapes regardless of fuel treatment (Fig. 6). On average, EFBR HRV simulations had $8.22 \text{ m}^2 \text{ ha}^{-1}$ (s.e. $0.127 \text{ m}^2 \text{ ha}^{-1}$) more BA than future RCP8 climates with no fuel treatments and no fire suppression (Fig. 6). The YCP landscape had less BA, CBD and PLFAS in the future because the more frequent fires converted lodgepole pine stands into grasslands and shrublands (Clark *et al.* 2017). On average, HRV simulations had $23.66 \text{ m}^2 \text{ ha}^{-1}$ (s.e. $0.216 \text{ m}^2 \text{ ha}^{-1}$) more BA than the RCP8/N simulations at YCP (Fig. 6). Once again, the NHB fuel treatment scenario resulted in less BA, CBD and PLFAS for CROWN and EFBR landscapes under both climates

except for the RCP8 scenario where it increased fire-adapted species in CROWN. For the RCP8 simulations, a moderate fire suppression level kept the simulations close to HRV conditions for the N and BAU FTE scenarios for the variable BA. For CBD, the simulations with zero fire suppression level and the N, BAU or FF FTE scenario were close to HRV conditions whereas for PLFAS, the highest suppression levels were necessary to be within HRV conditions for FF and BAU (Fig. 6). For BA, CBD and PLFAS, the effect of fire suppression was greater for the RCP8 simulations than the HIST simulations on the CROWN and EFBR landscapes (Fig. 6).

Discussion

The first step towards designing innovative and fully integrated fire management plans is to determine the most appropriate levels of suppression, wildland fire use and fuel treatments needed to create or maintain resilient landscapes into the future. In this study, we assumed that landscapes are resilient when they are within HRV, even into the future. Based on our results, we found that wildfires can be suppressed on some landscapes and still maintain conditions well within HRV, leaving the unsuppressed wildfires to be managed as wildland fire use. We also found that fuel treatments are needed only at high fire suppression levels (>80% fires suppressed) because wildland fire use can do most of the work of fuel treatments to maintain

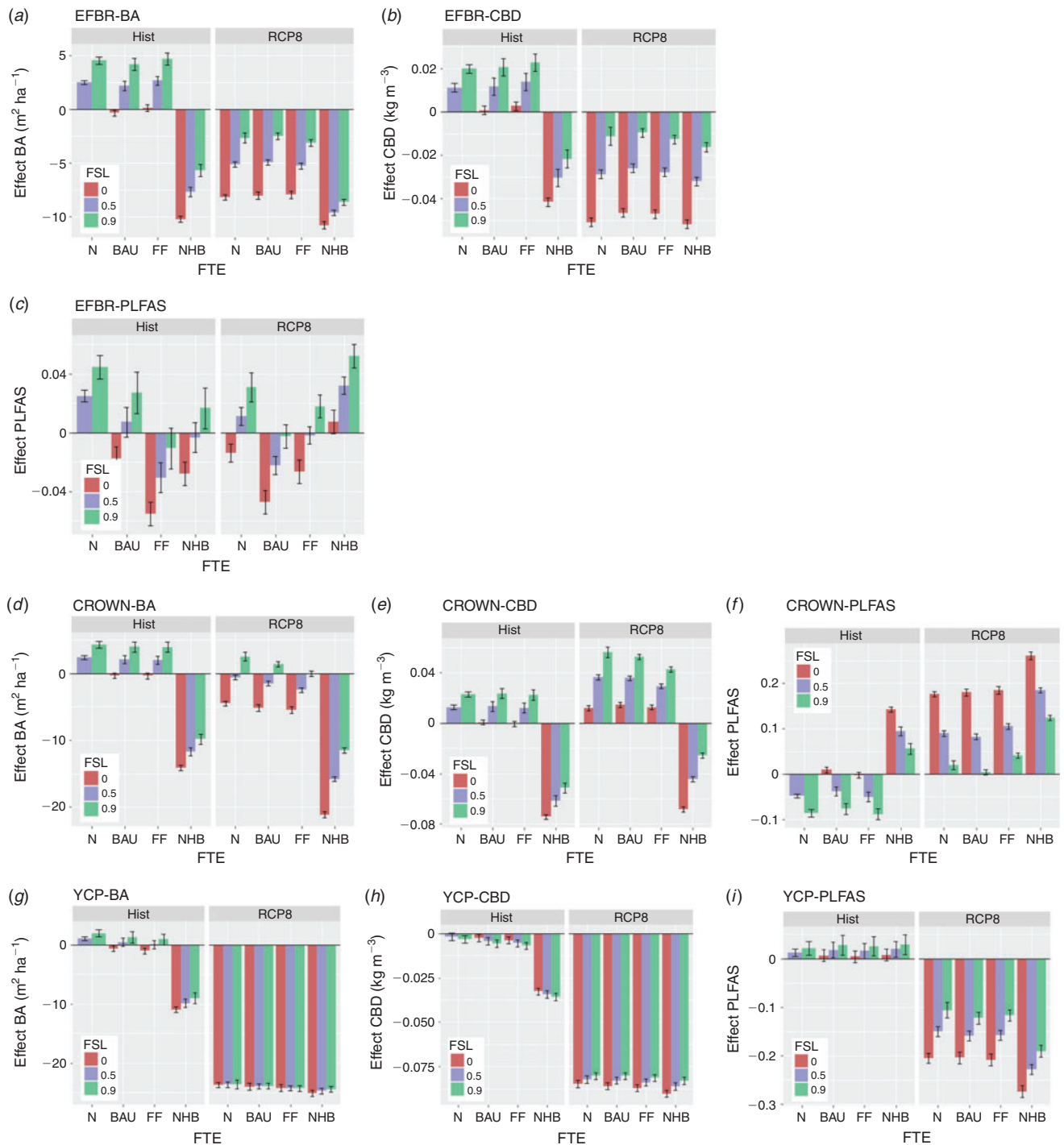


Fig. 6. Differences between historical range and variation (HRV) and each climate scenario (HIST, historical climate; RCP8, future climate under RCP8.5 scenario) and four fuel treatment efforts (FTE; BAU, business as usual; FF, fully funded; N, no treatments; and NHB, no holds barred) (Table 1) for a combination of three fire suppression levels (FSL) of 0.0, 0.5, and 0.9 for the variables basal area (BA), canopy bulk density (CBD), and percentage landscape in fire-adapted species (PLFAS) for all three study areas. The error bars are calculated as twice the standard error. Positive differences imply that HRV values were less than the FTE/Climate/FTE combination.

resilient landscapes. In fact, treating too much of the landscape (NHB effort) created conditions that were well outside HRV regardless of suppression level, except for the highest FSLs on

EFBR and CROWN landscapes (Fig. 5). Additionally, we discovered that fire suppression may actually keep landscapes within HRV under future RCP8 climates, while fuel treatments

offer minimal help in maintaining landscapes within HRV in the future (Fig. 5).

There are several other interesting findings in this study. First, it appears landscape setting greatly influences any potential FSL thresholds. We found that the most resilient landscape was the CROWN, a mixed-severity, moderately frequent fire regime, which stayed within HRV across most suppression levels for both HIST and RCP8 climates based on the PC1 values (Fig. 5). The fire-prone EFBR landscape, which experienced historically frequent fires, was resilient for fire suppression levels up to 40–50% for historical and above 50–60% for future climates for all fuel treatments except NHB (Fig. 5). The YCP landscape, which has a stand-replacement, infrequent fire regime, was the least resilient to the shift to RCP8 climate for all fire suppression levels and all fuel treatments (Table 3, Fig. 5). YCP was also the least affected by increases in fire suppression levels. These disparate findings are partially a result of two interacting factors: fire frequency and simulation time. Landscapes with frequent fires (EFBR) have many fires over the short simulation time, so a reduction in the number of fires may not significantly affect landscape dynamics over the 100 years of evaluation, whereas landscapes with long fire return intervals (YCP) had few fires during the simulation, and a reduction in these rare fires may cause significant changes in landscape dynamics.

Another finding is that the response variables used to assess resilience thresholds matter. In our analysis, we used a set of seven variables that were selected because we considered them important to fire management and they are often correlated with many other management-related variables (Table 1). We found that each of the seven variables had their own unique response when using HRV as reference (Table 2). And, when we collapsed all seven variables into one principal component (PC1), we found an entirely new set of resilience thresholds (Table 3). This indicates that the variables that are being assessed are extremely important to the analysis and that the set of representative variables must be carefully selected to match management objectives at the landscape scale to determine the right mix of wildfire, wildland fire use and fuel treatments. Moreover, single-variable analysis of thresholds might not fully represent the full suite of ecological interactions that occur over time, and multivariate analyses such as PCA may be a better option, albeit significantly more complicated.

The detected thresholds in suppression levels (FSL) were vastly different for historical climates (HIST) compared with future climates (RCP8), mainly because future climates are projected to be hotter and drier than today and therefore have increased fire (see Loehman *et al.* 2011a; Holsinger *et al.* 2014; Clark *et al.* 2017 for fire dynamics on these landscapes). In the present paper, we assumed that HRV is a good reference because it broadly represents those conditions under which most of the biota on the landscapes evolved and, as such, provides an ecologically viable benchmark for resilience (Keane *et al.* 2018). However, there is so much simulated fire on future landscapes (2.6–3.2 times burned area) that entirely new landscape structures were created when suppression levels dropped below 60% for our EFBR landscape. Therefore, we feel that the HIST and RCP8 simulation results can be used to find overlaps between HRV and a RCP8 future range of variation that can

provide possible management targets under new climates (Keane *et al.* 2018).

Fuel treatment efforts in the future must be designed and tailored to specific landscapes to be an effective means of maintaining resilience. We found that fuel treatment levels implemented in our simulation experiment were only effective at maintaining landscapes within HRV when fire suppression levels were high (>80% suppression levels) (Fig. 3a); wildfires that are allowed to burn seem to effectively treat fuels in today's and future landscapes. Although all of our simulated fuel treatments reduced fuel loadings and fire intensity, it took a great deal of treated area (>0.08% per year or ~10 000 ha) to offset impacts of fire suppression (Figs 3, 5). However, landscapes well outside HRV were created when too much of the landscape was treated (NHB scenario). Based on our results, it appears that the substitution of native fire regimes with fuel treatments will take a substantial investment in both effort and funding to treat over 1% of the landscape per year, especially on landscapes with frequent fire (EFBR) (Figs 3, 5). The level of fire suppression must be meticulously matched with area treated each year to maintain landscapes within HRV (Fig. 5). In Fig. 5, for example, it appears that approximately 1% of the landscape is needed to keep the EFBR landscape within HRV at the 40% resilience threshold, and, at the 90% suppression level, nearly >2000 ha (NHB scenario) must be treated annually to maintain HRV.

One of the most significant findings of this simulation experiment was that there were rarely obvious ecological 'tipping points' in FSL where a simulated landscape suddenly moved to a new stable state or type conversion; we mostly observed gradual changes in response variables that eventually moved the landscape outside HRV (Fig. 3). In ecological theory, a tipping point is when there is an abrupt change in an ecosystem quality, property or phenomenon, or where small changes in an environmental driver produce large responses in the ecosystem (Angeli *et al.* 2004; Scheffer *et al.* 2012). However, results of the ShewhartQCCs show that changes in landscape condition are gradual over time and there are few abrupt changes (Fig. 3). Qian (2014) also found that most ecological changes along temporal gradients were mostly gradual making strong threshold responses difficult to detect. This is probably a scale effect in our study as there were many stands on the three landscapes that reached a tipping point in some of the response variables, such as lodgepole pine to grassland conversions in the YCP (see Clark *et al.* 2017) or closed forest conversions to savanna in the EFBR (see Holsinger *et al.* 2014), but when aggregated to the landscape level, there was only a slow trend of the simulated landscape to some other condition. Because of this result, it is extremely important that a base case or benchmark condition (i.e. HRV) be selected to detect when a tipping point has occurred.

Limitations of this complex study warrant mention to properly interpret our results. First, the quantification of resilience using a simulated HRV time series has many weaknesses including the limited temporal depth in FireBGCv2 input parameters (e.g. weather, fire regime inputs) (Keane *et al.* 2011), subjectivity of variable selection, simulation design (only 100 years), and the great uncertainty in landscape modelling (Keane *et al.* 2018). Moreover, the assumption that the HRV envelope represents ecological resilience may not be entirely appropriate because there may be landscape conditions not represented in HRV that

are ecologically appropriate. Our arbitrary decision to use three standard deviations to detect any threshold violations is also a limitation in that our quantitative envelope is much bigger than most HRV bounds used in other studies (Keane *et al.* 2007, 2015a, 2009), and HRV may not be entirely appropriate for evaluating future ecological resilience (Keane *et al.* 2018).

In conclusion, we found that there are unique mixes of wildfire, wildland fire use and fuel treatments that maintain resilient landscapes into the future, but the target levels of each of these actions depend on the landscape, response variable(s) used for evaluation, representation of resilience (HRV in this study) and quantification of the resilience envelope (Shewhart QCC evaluations of three standard deviations from the mean in this study). Letting some wildfires burn under prescribed conditions may replace fuel treatments in remote wildland settings and may allow the suppression of fires in urban settings to maintain resilience at the landscape level. Finally, aggressive fuel treatment campaigns to mitigate effects of high fire suppression efforts may create landscapes that are well outside ecological resilience thresholds.

Conflict of interest

There were no conflicts of interests.

Acknowledgements

This research did not receive any outside funding. We thank Molly Retzlaff and Sarah Flanary, USFS Rocky Mountain Research Station Missoula Fire Sciences Laboratory, for extensive editing and quality control.

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