RESEARCH ARTICLE

For. Sci. 67(1):30–42
doi:10.1093/forsci/fxaa036

Fire & Fuels Management

Model Predictions of Postwildfire Woody Fuel Succession and Fire Behavior Are Sensitive to Fuel Dynamics Parameters

Maureen C. Kennedy, Morris C. Johnson, and Sarah C. Harrison

Computer models used to predict forest and fuels dynamics and wildfire behavior inform decisionmaking in contexts such as postdisturbance management. It is imperative to understand possible uncertainty in model predictions. We evaluated sensitivity of the Fire and Fuels Extension to the Forest Vegetation Simulator predictions to parameters that determine dynamics of standing dead trees (snags) and surface woody fuels. Predicted peak coarse and fine woody fuels were not sensitive to the decomposition rate of snags but were sensitive to decomposition rate of surface fuels regardless of initial snag density. Predictions of coarse woody fuel were sensitive to the snag fall rate when there was a higher initial density of snags. Fire behavior predictions were most sensitive to whether stylized fuel models or modeled fuels were used in calculations. When modeled fuels were used, fire behavior predictions were sensitive to the decomposition rate of surface fuels. Although this analysis does not inform the accuracy of model predictions, it does show where there is potential uncertainty in predictions of woody fuels succession and associated fire behavior. It is likely that any model that predicts postdisturbance fuel succession will also be sensitive to parameters that control snag dynamics and fuel decomposition.

Study Implications: Forest managers use computer models to help decide which actions to take to meet management objectives. Computer models have many settings and rules that affect predicted outcomes, and the values these settings should take are often uncertain. This study evaluates the consequences of such uncertainty on model predictions of future fuels following a high-severity fire. We show that model predictions are sensitive to the decomposition rate of small fuels and the snag fall rate. These results provide guidance for managers for which settings they should focus on when using these models and point to potential model improvements.

Keywords: salvage logging, sensitivity and uncertainty analysis, fuel succession, Fuel and Fire Effects extension to Forest Vegetation Simulator, FFE-FVS, fire behavior prediction

Episodic forest disturbances such as wildfire (Everett et al. 1999), drought (Allen et al. 2010), and insect outbreaks (Collins et al. 2012) can create large patches of dead standing trees (snags) in a landscape. These snags and associated large coarse woody debris (CWD) are essential for many species and provide multiple ecological functions (Bull et al. 1997, Hagan and Grove 1999, Brown et al. 2003), but they also potentially represent sources of fuel that may elevate future wildfire hazard (Peterson et al. 2015). It is important to understand trajectories of future woody fuels following disturbance (fuel succession; Agee and Huff 1987) and the potential effects of postdisturbance management such as salvage logging (Nemens et al. 2019) on future wildfire hazard.

Models are essential to inform the decisions of land managers and policymakers and for scientists to develop and test scientific hypotheses. The Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) is a computer modeling tool developed by the USDA Forest Service designed to simulate dynamic forest growth and development, fuel dynamics, fire behavior, and fire effects (Dixon 2012, Rebain et al. 2015). FFE-FVS has been used in scientific studies and to inform management decisions in contexts including the prediction of woody fuel succession after disturbance

Manuscript received May 5, 2020; accepted August 14, 2020; published online September 26, 2020.

Affiliations: *Maureen C. Kennedy (mkenn@uw.edu), School of Interdisciplinary Arts and Sciences, Division of Sciences and Mathematics, University of Washington–Tacoma, 1900 Commerce Street, Tacoma, WA 98402. Morris C. Johnson (morris.c.johnson@usda.gov) and Sarah Harrison (sch993@gmail.com), USDA Forest Service, Pacific Northwest Research Station, 400 North 34th Street, Suite 201, Seattle, WA 98103.*

Acknowledgments: *We thank Karen Honeycutt and James Pass. Sara Hwong, Anthony Martinez, Lesly Franco, and Claire Accettullo conducted field work for this project. We thank Vaagen Brothers Lumber Company for their support and collaboration. We also thank two anonymous reviewers and Chad Keyser for helpful comments that greatly improved this publication. Funding for this research was provided by the Northeast Washington Forest Vision 2020, Collaborative Forest Landscape Restoration, NEW Forest Vision 2020, Colville National Forest, USDA Forest Service, and Pacific Northwest Research Station. Two anonymous reviewers gave excellent comments that improved the manuscript.*

and to assess the impact of postwildfire management on future potential fire hazard (Brown et al. 2003, McIver and Ottmar 2007, Collins et al. 2012, Johnson et al. 2013, 2020). If a model is used to inform management decisions, it is important to understand possible sources of uncertainty in model predictions.

Computer models such as FFE-FVS can be complicated, comprising thousands of lines of computer code that include mathematical representations of relationships among variables that may change dynamically over space and time. Model parameters are constant values that define the specific shape of a mathematical relationship when applied to a particular system (e.g., the decomposition rate of a particular fuel type). These parameters are not estimated without error and thereby have uncertainty in their values that propagates to uncertainty in the model predictions (O'Neill et al. 1980). It is important to understand how model parameter uncertainty may affect uncertainty in model predictions, particularly if a model is used to inform forest management decisionmaking.

There are three main sources of uncertainty in model predictions (O'Neill and Gardner 1979, Beck 1987, Turley and Ford 2009): data uncertainty (including data used for parameter estimation and model input data), model structural uncertainty (internal model mathematical and algorithmic structure), and natural variability and stochasticity. Sensitivity analysis is a model uncertainty assessment method (Hamby 1994, Pianosi et al. 2016) that enables the ranking of model parameters by their relative influence on chosen model predictions, to quantify model prediction uncertainty, and to conduct model assessment by highlighting areas where the model does not perform as expected (thereby clarifying the modeling applicable domain; US Environmental Protection Agency, Office of the Science Advisor 2009). Sensitivity analysis is not a model accuracy assessment per se, but rather it helps us to understand how uncertainty in model parameter values and data inputs might affect model predictions, in the context of the underlying model structure. It also highlights parameter uncertainty that is consequential to model predictions and where resources for model development and deployment should be concentrated.

With such a model as FFE-FVS, a full exploration of all possible model parameters is both computationally and cognitively intractable. Rather, parameters can be grouped into subsets that inform particular modeling questions (e.g., McElhany et al. 2010). For example, Hummel et al. (2013) performed a sensitivity analysis of FFE-FVS mortality predictions on three main model settings—fuel loading input, fuel moisture, and wind speed—and whether the disease module was on. They found that the model was more sensitive to the moisture and wind speed settings than to how fuels were inventoried. They recommended resources be dedicated to better estimate moisture and wind inputs when using FFE-FVS to predict mortality. Johnson et al. (2011) performed what was essentially a sensitivity analysis by simulating different thinning and surface fuel treatments using FFE-FVS. They found that FFE-FVS predictions of fire behavior were insensitive to two different types of surface fuel treatments that would be expected to result in different fire behaviors, thereby identifying a target for model improvement.

Objectives

The overarching goal of this study was to understand how sensitive model predictions of woody fuel dynamics and future fire behavior are to uncertainty in a subset of model parameters. These results will thereby inform future applications of FFE-FVS for fuels succession studies, as well as point to general drivers of fuel dynamics that might be sources of uncertainty for other models that are used to inform postfire management. The results presented will improve understanding of key uncertainties in model predictions and provide guidance for managers when choosing model settings. Researchers can use this analysis to point to areas for model improvement. Our specific objectives were as follows:

1. To identify the snag and woody fuel settings that most influence fuel loadings and fire behavior predictions in FFE-FVS, in the context of initial snag density.
2. To determine if FFE-FVS is sensitive to how fuels are represented in fire behavior calculations and if it is sensitive to data input uncertainty.

Methods

Study Areas

We used postfire fuel loading and snag data from two recent fires in the Western United States: the 2015 Stickpin Wildfire in the Colville National Forest in northeastern Washington State (hereafter Stickpin) and the 2014 King Wildfire in the Eldorado National Forest in central Sierra Nevada California State (hereafter King). Data collection protocols were similar at both locations. For Stickpin, details can be found in Johnson et al. (2020). Following Stickpin, some areas that experienced 100 percent basal area (BA) mortality were salvage logged. Salvage logging treatments had been planned but not implemented following the King Fire. For Stickpin, posttreatment snag and surface fuel loadings were used to initialize FFE-FVS simulations. For King, second-year measurements were used to initialize FFE-FVS simulations. Here we give brief descriptions of the study areas and the sampling methods.

The Colville National Forest is within the Okanagan Highland geologic province (USDA 2014). Douglas-fir (*Pseudotsuga menziesii* [Mirb.] Franco) and western larch (*Larix occidentalis* Nutt.) are the dominant forest types. Lodgepole pine (*Pinus contorta* Douglas ex Loudon) and ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson) are also present (Pass and Corvino 2014). The Eldorado National Forest lies in the central Sierra Nevada on the western slope of the mountain range. The area has pine-dominated Sierra mixed conifer forests, true fir forests, chaparral, and conifer plantations. This includes oak woodlands, gray pine (*Pinus sambiniana*), ponderosa pine (*Pinus ponderosa*), and knobcone pine (*Pinus attenuata*) with a shrub/grasslands understory component at low elevations. Mixed conifer stands of ponderosa pine, white fir (*Abies concolor*), incense cedar (*Calacedrus decurrens*), and black oak (*Quercus kelloggii*) are found at higher elevations (Hutchins and Barker 1989, USDA Forest Service 2015).

At both sites, a full generalized randomized block sampling design was used. Here, we used stand data from all treatment and block combinations. This resulted in nine stands associated with Stickpin and 15 associated with King. At plot center, species, diameter at breast height (DBH; cm), total height (m), and tree crown base height (m) were recorded for each snag >11.4 cm DBH within a 202 m^2 circular, fixed-area plot. Data for snags <11.4 cm DBH were recorded on an 81 m^2 plot. Woody fuel loadings were estimated using the planar-intercept method as described by Brown (1974) on four 12 m planar transects originating from random azimuths. Angles were not corrected for slope. One-hour fuels were sampled at 10.8–12 m; 10-hour fuels, 9–12 m; and 100- and 1,000-hour fuels, 0–12 m along the transect.

Summaries of initial conditions associated with each fire are given in Table 1. King had higher initial snag BA and quadratic mean diameter than Stickpin. Values for initial woody fuel loading overlapped between the two fires, although Stickpin had a higher upper bound for CWD (Table 1). Higher CWD loadings in the Stickpin area were associated with stands that had been salvage logged following the wildfire (Johnson et al. 2020).

FFE-FVS Model Settings

We used the Inland Empire variant of FFE-FVS (Rebain et al. 2015, Keyser 2019) for Stickpin and the Western Sierra variant (Keyser and Dixon 2019) for King. FFE-FVS integrates three submodels to simulate fuel succession and potential wildfire behavior. The snag submodel computes snag breakage and fragmentation, snag decay, and snag fall. The fuel submodel calculates the accumulation and decomposition of dead woody fuel (surface fuels). The fire submodel estimates surface fire intensity using the semiempirical FIREMOD, based on existing models (Rothermel 1972, Albini 1976, Andrews 1986). Crown fire is simulated using Scott and Reinhardt (2001), which couples the Rothermel (1972) model of surface fire spread with the Van Wagner (1977) model of crown fire initiation. Fire effects predictions (such as tree mortality) are adapted from FOFEM (first order fire effects model; Reinhardt et al. 1997, Rebain et al. 2015, Lutes 2017). Dynamics of live understory fuels including herbaceous vegetation and shrubs are not simulated in FFE-FVS. For fire behavior calculations, these loadings are specified by the stylized fuel model selected during the dynamic simulation.

All FFE-FVS simulations were initialized with woody fuels and snag data. Artificial reforestation was simulated with a postfire planting of 420.1 trees ha^{-1} conifer seedlings. The stands were projected for 80 years (2017–2097) without a simulated wildfire to predict woody fuel accumulations. Simulations were repeated with a simulated wildfire at year 2037 (20 years after salvage logging) to assess sensitivity of fire behavior predictions. Model predictions were returned every five years, with additional outputs one year before and one year after the simulated wildfire. The wildfire for Stickpin was simulated with the 90th percentile fire weather inputs: 4 percent 1-hour and 10-hour fuel moistures, 5 percent 100-hour fuel moisture, 10 percent 1,000-hour fuel moisture, 15 percent duff moisture, and 70 percent live woody and herb moisture. The wildfire for King was simulated with the following fuel moistures: 3 percent for 1-hour, 4 percent for 10-hour, 5 percent for 100-hour, 6 percent for 1,000-hour, 30 percent for duff, 69 percent for woody, and 30 percent for herbaceous. The temperature for Stickpin was 37.8°C, and the temperature for King was 36.7°C. Both were simulated with 32 kph wind speed. All settings not detailed here were set to FFE-FVS default values.

Model Outputs and Sensitivity Analysis Experimental Design

We recorded the peak predicted CWD (1,000-hour and larger) and fine woody debris (FWD; 1- to 100-hour) over the simulation without wildfire to represent fuel accumulation. For fire behavior, we recorded the predicted rate of spread (ROS) and flame length (FL) the year before the simulated wildfire.

We conducted a local (one at a time) sensitivity analysis on three parameters important to the fire and fuels submodels (described in Rebain et al. 2015). The snag decay rate controls the rate at which snags decay from solid (initial state; "hard") to rotten (ending state; "soft"). The snag fall rate controls the rate at which snags transition from standing to surface fuels. The decomposition rate controls decomposition of surface fuels. FFE-FVS designates default values for these rates depending on the region and species. In general it is preferable to use parameter error estimates to sample a plausible parameter space for sensitivity analysis, but FFE-FVS documentation does not provide such error estimates. The user may elect to apply a multiplier to adjust these default rates, where a value of 1 returns the default rate, 0.5 returns half the default rate, and 1.5 returns 1.5x the default rate, and so forth. For the sensitivity analysis, we simulated model outputs at the default values, then at default multipliers of 0.33, 0.5, 0.67, 1.33, 1.5, and 1.67. In this local sensitivity analysis, parameters were modified individually with the remaining parameters set at default values (Table 2).

We used two methods available in FFE-FVS to enter fuels for fire behavior calculations. In the first, FFE-FVS uses current predicted conditions to classify the stand into two of the Scott and Burgan (2005) set of 40 stylized fuel models (hereafter FM40), with a relative weighting assigned to each fuel model for that stand. FFE-FVS assigns a weighting for each fuel model in each stand. In the second, FFE-FVS uses modeled fuel loads directly in fire behavior calculations (hereafter Modeled). If modeled fuel loadings are selected, then the surface area to volume ratios for 1-hour, herbaceous, and live woody fuels are either set to a user-specified value or given a default value (6,562, 5,906, and 4,921 m^{-1} for each, respectively). Bulk density for live and dead fuels is either user specified or set to default (1.6 and 12.0 kg m^{-3} for live and dead, respectively). The dead fuel moisture extinction coefficient is based on the bulk density value and the particle density (default 513 kg m^{-3}). We did not modify these values from default settings for modeled fuels.

Sensitivity results were summarized by calculating Pearson's correlation coefficient between the default rate multiplier and each model output. These were calculated separately for each fire. Fire behavior calculation correlations were also calculated separately for FM40 and Modeled fuels. The correlation coefficient measures the

Table 1. Summary of initial snag basal area (BA) and quadratic mean diameter (QMD) and initial coarse and fine woody fuel loading (CWD, FWD) for each wildfire. Mean values, standard deviations (sd), and ranges are given. Number of stands measured in each wildfire is given next to the fire name in parentheses.

	BA (m^2 ha^{-1})		QMD (cm)		CWD (Mg ha^{-1})		FWD (Mg ha^{-1})	
	mean (sd)	(min, max)	mean (sd)	(min, max)	mean (sd)	(min, max)	mean (sd)	(min, max)
Stickpin (9)	13.9 (9.6)	(4.0, 29.3)	21.1 (8.7)	(10.2, 34.9)	13.7 (8.5)	(5.9, 33.7)	4.1 (2.8)	(0.49, 7.7)
King (15)	63.8 (11.7)	(38.8, 81.0)	41.6 (12.9)	(22.6, 66.8)	7.8 (2.3)	(4.4, 13.1)	4.8 (1.5)	(2.0, 7.7)

Table 2. Sensitivity analysis experimental design. This design is repeated for each stand in each fire and with stylized and modeled fuels. DECOMP is the decomposition rate of surface woody fuels, SNAGD is the snag decay rate, and SNAGF is the snag fall rate. Values are multipliers of the default value in Fuel and Fire Effects extension to Forest Vegetation Simulator, where a multiplier value of *x* indicates a rate *xdefault.**

DECOMP	SNAGD	SNAGF
1	1	1
1	0.33	1
1	0.5	1
1	0.67	1
1	1.33	1
1	1.5	1
1	1.67	1
1	1	0.33
1	1	0.5
1	1	0.67
1	1	1.33
1	1	1.5
1	1	1.67
0.33	1	1
0.5	1	1
0.67	1	1
1.33	1	1
1.5	1	1
1.67		1

strength of the linear relationship between the rate multiplier and the model output. Although some relationships were not linear, the correlation still gives a relative measure of the strength and direction of the relationship.

Results

Woody Fuel Succession

Sensitivity patterns for predicted peak woody fuels were similar between the two wildfires. Predicted peak CWD did not change with increasing snag decay rate, with correlations near zero (Figure 1; Table 3). Predicted peak CWD had moderate positive correlations with snag fall rate, where the correlation for King was more than twice that for Stickpin (Figures 1, 2; Table 3). The predicted peak CWD had moderate to strong negative correlations with decomposition rate for both fires. The predicted peak CWD was sensitive to the initial density of snags. In general, predicted peak CWD increased with increasing initial snag BA (Figure 1). There was an interaction, however, between snag fall rate, initial snag BA, and peak CWD. Comparisons among stands with different initial snag BA sometimes differed by snag fall rate.

The predicted peak FWD did not change with snag decomposition or snag fall rates (Figure 2; Table 3), with correlations near zero for both fires. Predicted peak FWD was most sensitive to the decomposition rate, with strong positive correlations. Predicted peak FWD was less sensitive to the initial snag BA than predicted peak CWD, although higher predicted peak FWD was generally associated with higher initial snag BA (Figure 2).

Fire Behavior

Regardless of scenario, neither predicted ROS nor predicted FL was sensitive to the snag decay or fall rate (Figures 3–6; Table 3) with correlations near zero for both fires. Predicted fire behavior sensitivity to the decomposition rate varied by the fuel scenario. With modeled fuel loadings, both predicted ROS and FL decreased with increasing decomposition rate for both fires (Figures 4–6; Table 3). The negative relationship leveled off when the decomposition rate was above the default value. Both ROS and FL were predicted to be lower for Stickpin than for King when modeled fuels were used.

The relationship between predicted fire behavior and decomposition rate was more complicated when fuels were classified into one of the 40 stylized fuel models (FM40). When stylized fuel models were used, ROS was predicted to be higher for Stickpin than King, whereas FL was predicted to be lower. For Stickpin, there were pronounced differences in predicted ROS and FL between FM40 and modeled fuels (Table 3; Figures 3, 5). With FM40, predicted ROS increased then leveled off with increasing decomposition for Stickpin. FL had a flatter relationship with increasing decomposition rate for Stickpin. ROS and FL for Stickpin were predicted to be higher for FM40 than when modeled fuels were used.

For King, the predicted ROS and FL were more similar between the fuel scenarios than for Stickpin (Figures 4, 6). When decomposition was below default with FM40, predicted ROS for King decreased with increasing decomposition parallel to the modeled fuel pattern. When decomposition was above default, predicted ROS for King increased and then leveled off with increasing decomposition (Figure 4). For King, FL followed a consistent decreasing pattern with increasing decomposition rate for FM40, similar to when modeled fuels were used (Figure 6).

There was little variability in the stylized fuel model combinations chosen by FFE-FVS for each fire (Table 4), although the two fires differed in which sets were chosen. For Stickpin, FFE-FVS chose the combination of GR2/GS1 (grass/grass-shrub) stylized fuel models in 72.5 percent of the scenarios and combinations involving grass and shrub fuel models in 96.3 percent of the scenarios. For King, FFE-FVS chose the combination of TL6/SB6 (timber-litter/slash-blowdown) stylized fuel models in 72.1 percent of the scenarios and combinations involving shrub, timber-litter, and slash-blowdown fuel models in 88.3 percent of the scenarios.

Discussion

Episodic forest disturbances such as drought, insects, and wildfire can leave large areas of high-density dead standing wood. When considering postdisturbance management, it is important to have credible predictions of the future conditions of these areas. Among the ecological benefits of snags and associated CWD, one major concern is that current high snag density could cause future hazardous wildfire conditions (Coppoletta et al. 2016, Nemens et al. 2019). Woody fuel succession following wildfire is determined by a balance between fuel accumulation and fuel loss (Peterson et al. 2015). Model structures that predict future fuel accumulations have dynamics that describe fuel accumulation through mortality, initial biomass, and snag fall and loss through decomposition or combustion. The details of these model structures will differ, but they can be reduced to these basic processes. Here we found that predictions of future woody fuels are sensitive to the initial snag BA, the snag fall rate, and the decomposition rate of surface fuels in a way that is consistent with these basic dynamics.

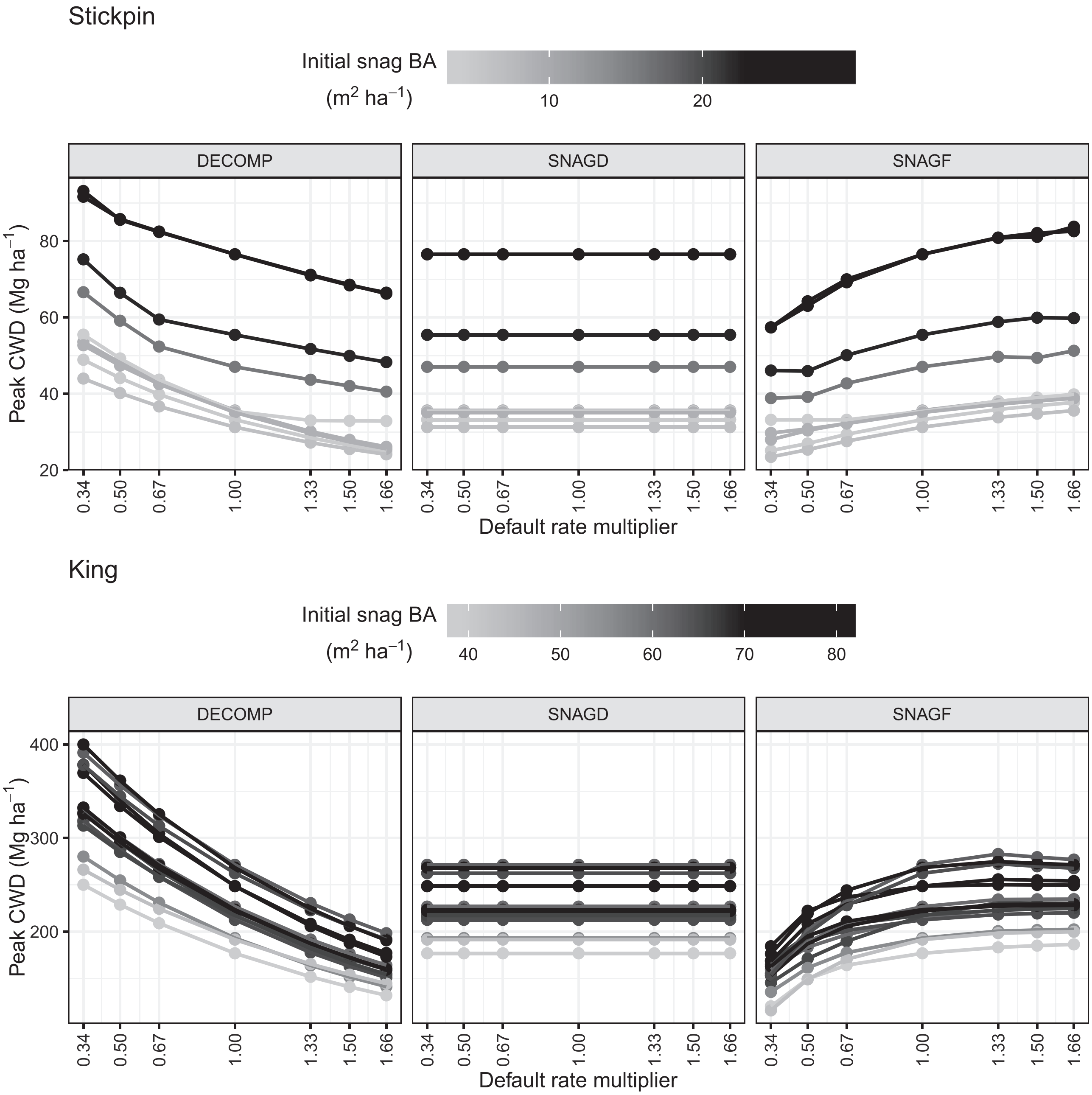

Figure 1. Predicted peak coarse woody debris (CWD) with increasing default multipliers for snag decomposition (DECOMP), snag fall (SNAGF), and decomposition (SNAGD) rates for stands with variable initial snag basal area (BA) for Stickpin and King. A multiplier value of *x* indicates a rate *xdefault. One fuel model scenario is pictured because fuel model scenario does not modify peak fuel loadings.**

Table 3. Pearson's correlation coefficients between each model parameter and each model output for each fire. DECOMP is the decomposition rate of surface woody fuels, SNAGD is the snag decay rate, and SNAGF is the snag fall rate. FM40 refers to the 40 stylized fuel model scenario; Modeled refers to predicted fuels entered directly in calculations. CWD and FWD are coarse and fine woody debris, respectively. ROS is rate of spread, and FL is flame length.

	Stickpin			King		
	SNAGD	SNAGF	DECOMP	SNAGD	SNAGF	DECOMP
Peak CWD	0.00	0.31	–0.46	0.00	0.67	–0.88
Peak FWD	–0.02	0.04	–0.93	–0.05	0.00	–0.84
ROS (FM40)	0.00	0.00	0.75	0.02	0.00	–0.73
ROS (Modeled)	–0.01	0.00	–0.76	0.03	0.00	–0.93
FL (FM40)	0.00	0.00	0.47	0.01	0.00	–0.92
FL (Modeled)	0.00	0.00	–0.79	0.03	0.00	–0.92

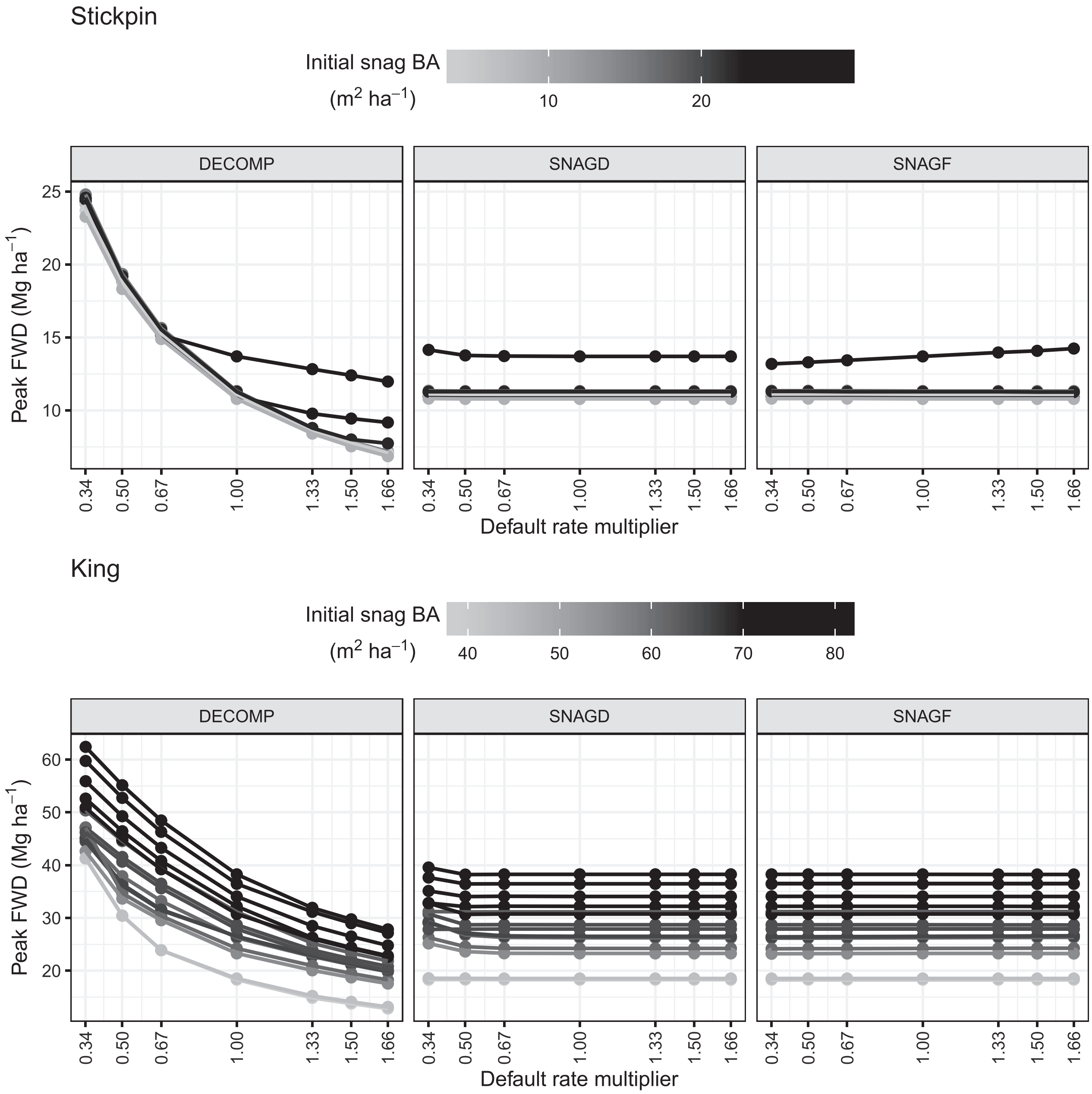

Figure 2. Predicted peak fine woody debris (FWD) with increasing default multipliers for snag decomposition (DECOMP), snag fall (SNAGF), and decomposition (SNAGD) rates for stands with variable initial snag basal area (BA) for Stickpin and King. A multiplier value of *x* indicates a rate *xdefault. One fuel model scenario is pictured because fuel model scenario does not modify peak fuel loadings.**

Predicted Peak Woody Fuels

Postdisturbance management such as salvage logging reduces the BA of the standing dead wood relative to pretreatment conditions and nearby untreated areas (McIver and Ottmar 2007, Collins et al. 2012, Ritchie et al. 2013). Unsurprisingly, since the snag BA represents the pool of woody fuels that can possibly accumulate on the ground, as it increases so does predicted peak woody fuels (Figures 1, 2; McIver and Ottmar 2007, Ritchie et al. 2013, Peterson et al. 2015). A manager might be interested in how retained snag BA relates to target woody fuel accumulations (Ritchie et al. 2013). This can be informed by model predictions that are subject to parameter uncertainty. McIver and Ottmar (2007) compared FFE-FVS–predicted woody fuels at different decomposition and fall rates for a single stand. From their simulations, they surmised that the rates would only affect the magnitude and timing of fuel loadings, not comparisons among scenarios. In contrast, by evaluating the sensitivity of predicted fuels for stands with varying snag BA, we found that sensitivity of peak CWD to the snag fall rate may change with the initial snag BA (Figure 1). Comparisons of management scenarios for future predicted coarse woody fuels would thereby be complicated by uncertainty in the snag fall rate. This has implications for management decisions for the target-retained snag BA. Snag fall rate itself is predicted by species, diameter, and mortality agent (Everett et al. 1999, Acker et al. 2013, Ritchie et al. 2013). For planning purposes, the range of plausible snag fall rates for a given area should be considered in evaluating management targets for peak coarse woody fuel loadings.

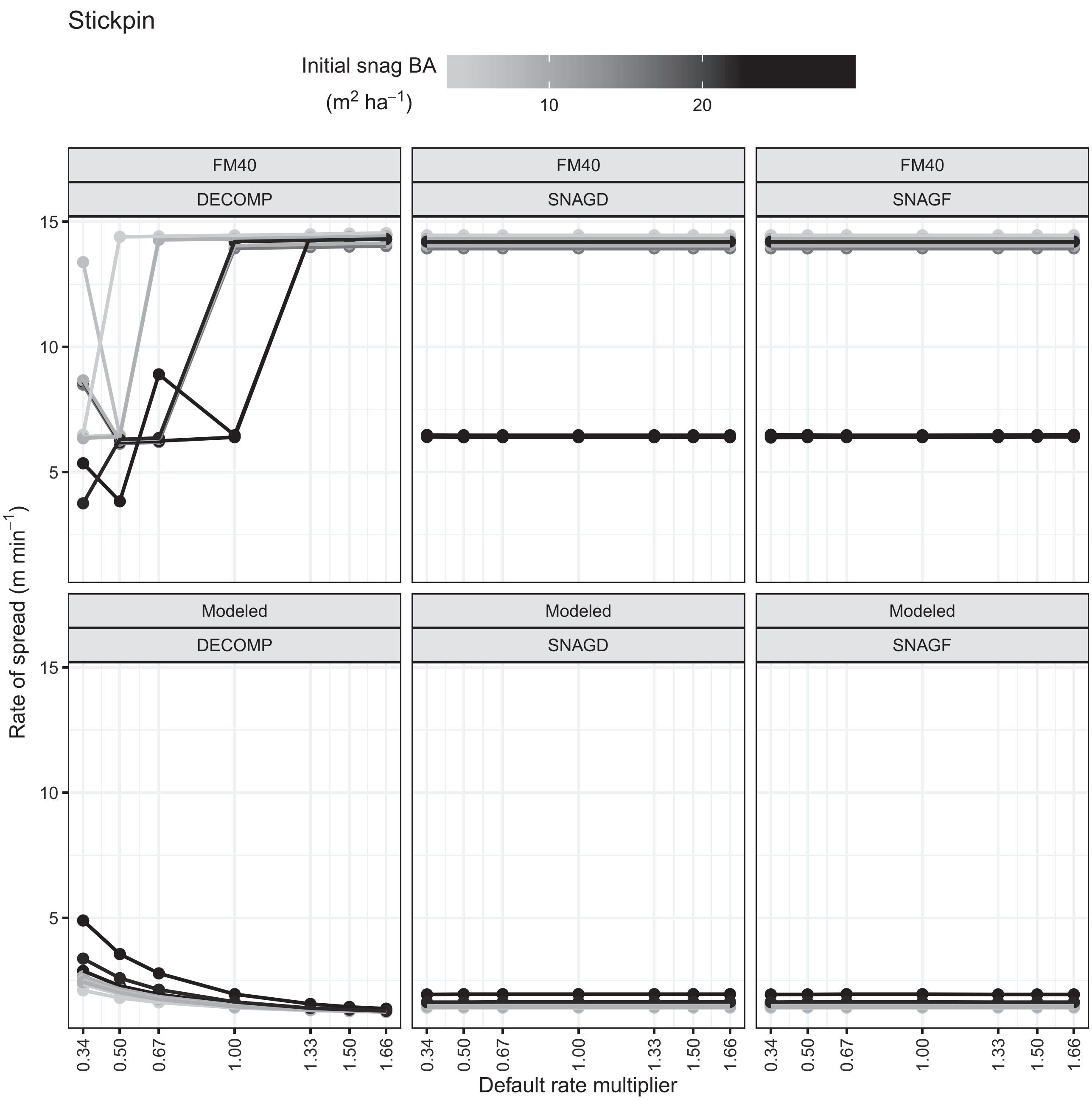

Figure 3. Predicted rate of spread (ROS) predicted at model year 20 with increasing default multipliers for snag decomposition (DECOMP), snag fall (SNAGF), and decomposition (SNAGD) rates for Stickpin. FM40 indicates the 40 stylized fuel model scenario; Modeled indicates predicted fuel loadings are entered directly into fire behavior calculations. A multiplier value of *x* indicates a rate *xdefault.**

Predicted peak woody fuel was strongly sensitive to decomposition rate (Table 3; Figures 1, 2). For a given snag BA, predicted peak woody fuels decreased with increasing decomposition rate (Figures 1, 2; McIver and Ottmar 2007) as decay outpaced accumulation. In general, stands with higher initial snag BA resulted in higher predicted woody fuel loadings compared with stands with lower initial snag BA. This implies that comparisons among management scenarios would not be affected by uncertainty in decomposition rate (McIver and Ottmar 2007). The predicted magnitudes of peak woody fuels, however, would be affected (Figure 1).

With projected climate change, the strong sensitivity of predicted peak woody fuel loadings to decomposition rate may be more consequential for management decisions than other parameter sensitivities. In FFE-FVS, decomposition rate is fixed during a given simulation. Even if these rates are assumed to be specified without error, decomposition rate increases with increasing moisture and temperature (Moore 1986, Gholz et al. 2000). This implies increased decomposition under a climate warming scenario and uncertain changes to decomposition because of changes to precipitation regimes and surface fuel moisture. These dynamics are not currently incorporated in the FFE-FVS model structure. An increase in decomposition rate with increasing temperature could result in a reduction in surface woody fuel loading as loss to decomposition increases relative to accumulation. This illustrates potential indirect feedbacks between future climate change and fire hazard (Matthews et al. 2012). It is necessary to account for these additional sources of uncertainty in decomposition rate to give robust predictions of future woody fuels and associated fire behavior.

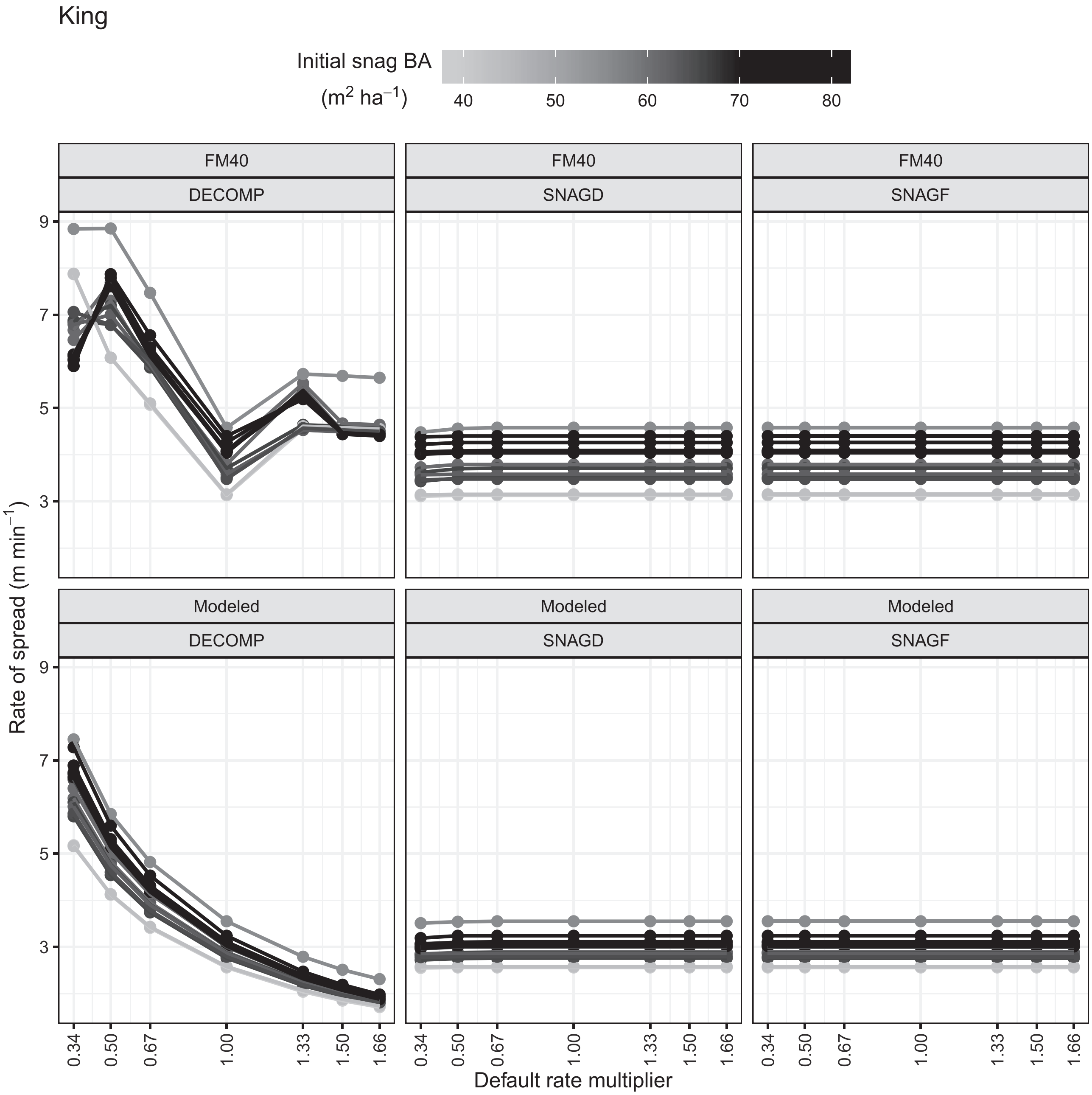

Figure 4. Predicted rate of spread (ROS) predicted at model year 20 with increasing default multipliers for snag decomposition (DECOMP), snag fall (SNAGF), and decomposition (SNAGD) rates for King. FM40 indicates the 40 stylized fuel model scenario; Modeled indicates predicted fuel loadings are entered directly into fire behavior calculations. A multiplier value of *x* indicates a rate *xdefault.**

Postdisturbance management is not solely concerned with hazardous fuel accumulation (Nemens et al. 2019). Although predicted peak woody fuels did not change with the snag decay rate, the snag decay rate would influence the distribution of snags across decay classes, which may be important for management of some wildlife species (Raphael and White 1984). If FFE-FVS is used to predict wildlife habitat rather than future fire hazard and fuel succession, an analysis of how uncertainty in snag decay rate propagates to predictions of snag decay class would be warranted.

Predicted Fire Behavior

The sensitivity of the predicted peak woody fuels followed a pattern that is consistent with the basic dynamics of fuel succession (Figure 1). These changes to woody fuel loadings would be expected to cause concomitant changes to predicted fire behavior, yet we did not find a simple connection between them (Figures 3–6). There are two main explanations to be found in the structures of the models used to predict fire behavior in FFE-FVS: the use of stylized fuel models (Scott and Burgan 2005) as input to the fire behavior models and coarse woody fuels not included in the Rothermel (1972) calculation of fire intensity.

Stylized fuel models were developed to give representative fuel types that produce general assessments of fire behavior that are not expected to represent actual fuel loadings and associated characteristics (Keane 2013). It has been recognized that these fuel models lack sensitivity to changes in woody fuel amounts (Sandberg et al. 2007, Johnson et al. 2011, Noonan-Wright et al. 2014)

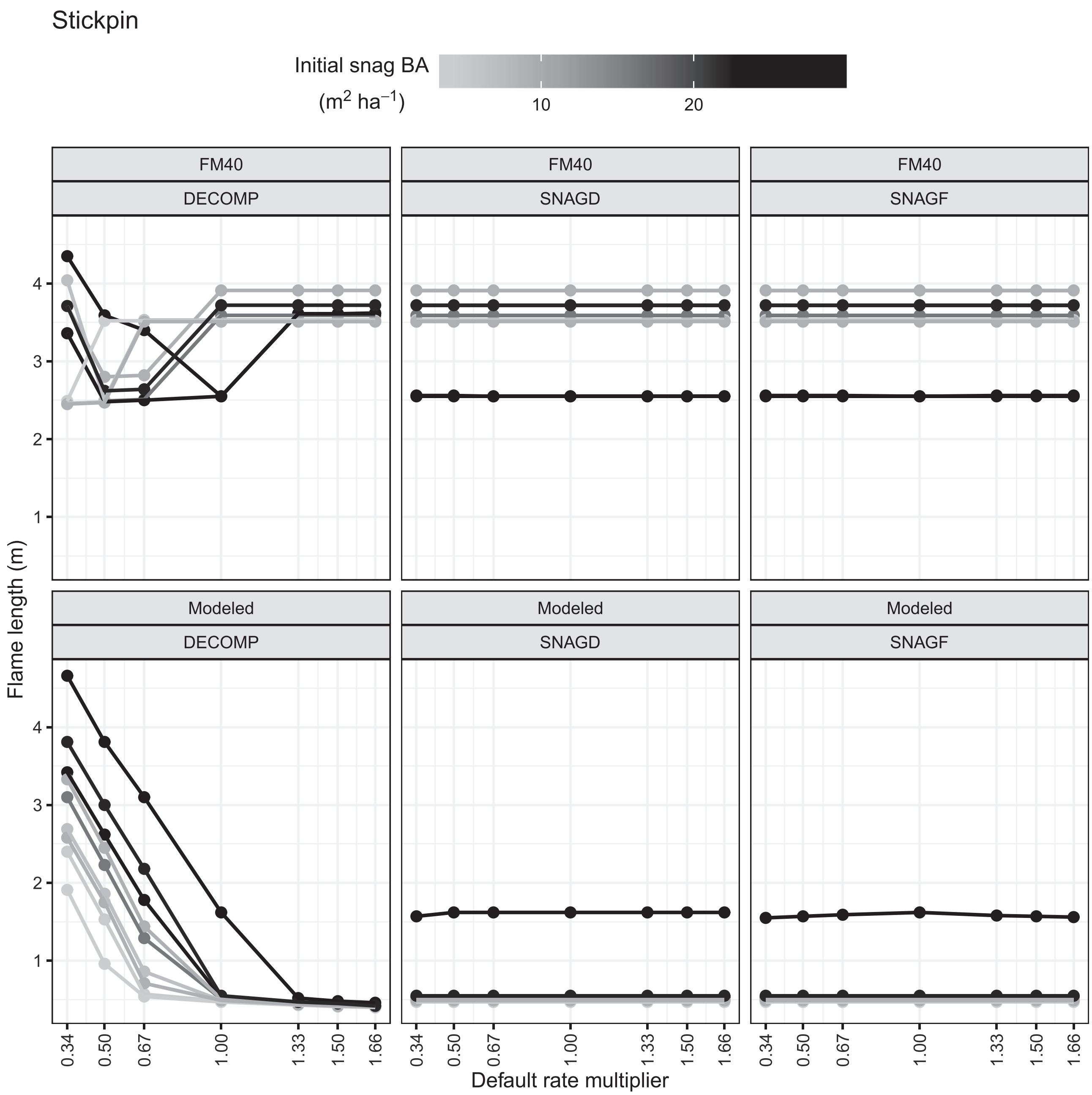

Figure 5. Predicted flame length (FL) predicted at model year 20 with increasing default multipliers for snag decomposition (DECOMP), snag fall (SNAGF), and decomposition (SNAGD) rates for Stickpin. FM40 indicates the 40 stylized fuel model scenario; Modeled indicates predicted fuel loadings are entered directly into fire behavior calculations. A multiplier value of *x* indicates a rate *xdefault.**

and indeed we found that here (Table 3; Figures 3–5). Across all the scenarios we evaluated, FFE-FVS selected a small number of unique fuel model combinations (Table 4). Selection of an appropriate fuel model is a major source of error when using fuel models to assess fuel treatments (Varner and Keyes 2009). Fuel loadings are dynamic in space and time (Keane et al. 2012) and exhibit high variability for a given vegetation classification (Prichard et al. 2019). When fuel beds are coarsened to a discrete set of stylized fuel models, the variability in fuel loading will be less than that actually on the ground. This implies that a given fuel model could possibly represent wide bands of woody fuel loadings and therefore a range of associated plausible fire behaviors. Yet, with fixed environmental conditions, one fuel model would predict single values for fire behavior metrics.

There is no easy answer to the known issues in using stylized fuel models to predict fire behavior when fuel loadings are dynamic and variable. Custom fuel models may be created based on measured or predicted loadings and fuel characteristics (Burgan and Rothermel 1984). Custom fuel models, however, might not result in credible fire behavior predictions if they are not calibrated (Burgan and Rothermel 1984, Cruz and Fernandes 2008). Fire behavior is highly sensitive to characteristics such as bulk density (BD), surface area to volume ratio (SAV), and dead fuel moisture extinction (Burgan and Rothermel 1984, Burgan 1987). Measurement of these characteristics in a manner appropriate for use in a fire behavior model is not trivial (Cruz and Fernandes 2008), and it is difficult to predict them dynamically in a model such as FFE-FVS (Rebain et al. 2015) as predicted fuel loadings change.

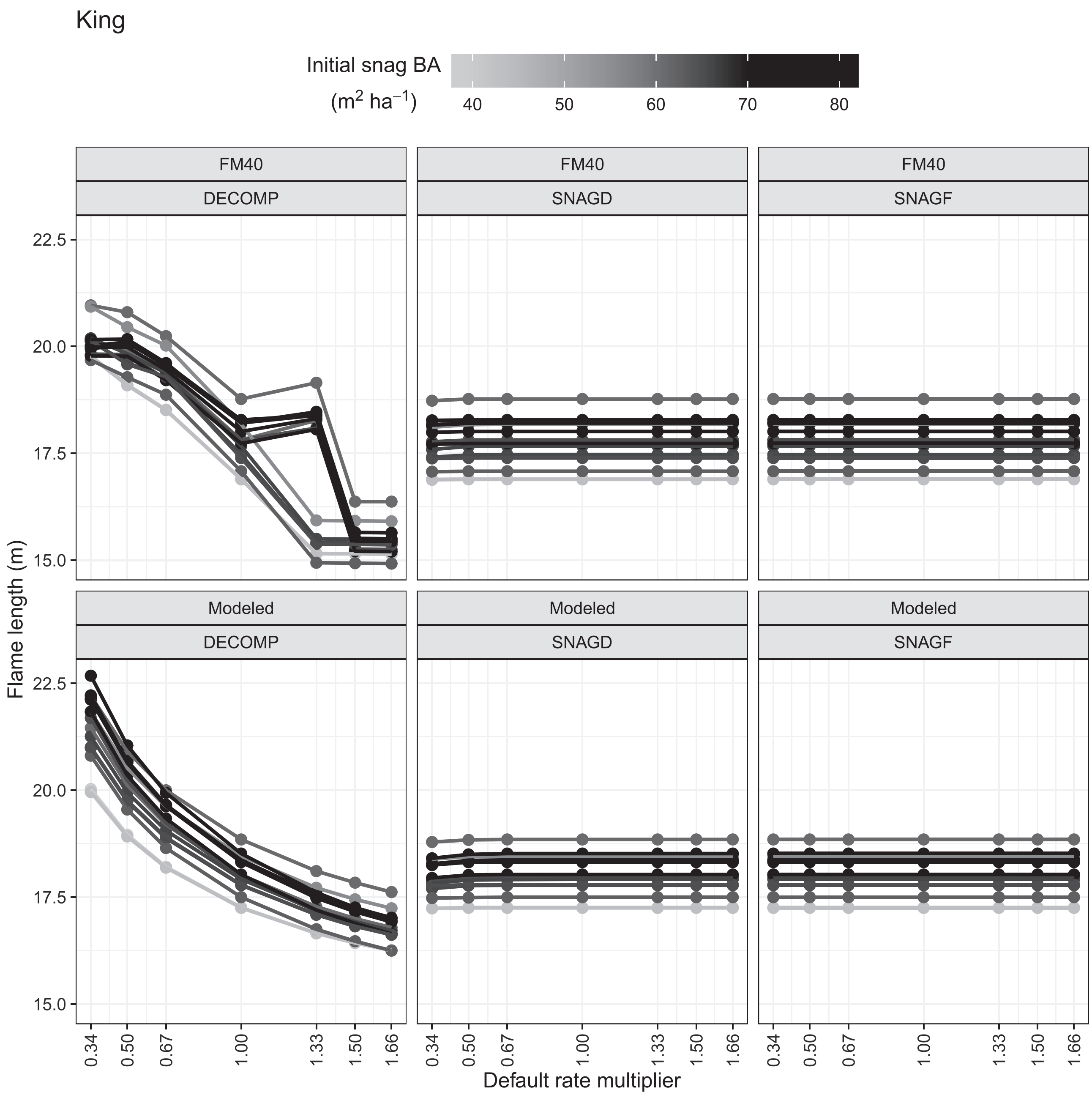

Figure 6. Predicted flame length (FL) predicted at model year 20 with increasing default multipliers for snag decomposition (DECOMP), snag fall (SNAGF), and decomposition (SNAGD) rates for King. FM40 indicates the 40 stylized fuel model scenario; Modeled indicates predicted fuel loadings are entered directly into fire behavior calculations. A multiplier value of *x* indicates a rate *xdefault.**

When using modeled fuels in our analysis, we accepted the default settings for BD, SAV, and moisture extinction. The consequences of this choice differed depending on the set of fuel models chosen by FFE-FVS. For Stickpin, this resulted in persistently lower predicted ROS and FL than when stylized fuel models were used (Figures 3, 5). For King, the results were more similar between the two fuel scenarios (Figures 4, 6). Noonan-Wright et al. (2014) also found comparisons between custom and stylized fuel models in FFE-FVS depended on the stand conditions (pre- or postfuel treatment). Fire behavior metrics such as ROS and FL are not necessarily expected to increase monotonically with fine fuel loading (Burgan 1987) because loading interacts with other fuel characteristics that affect fire behavior. It is important to characterize the whole fuel bed as fuel loadings change. If custom fuel models are used to accommodate dynamic fuel loadings, it is important to properly calibrate the fuel characteristics. Calibration itself is not a trivial process.

Calibration is a common tool to determine values for model parameters that are either difficult or impossible to measure. Fuel model calibration has been performed allowing for variability across fuel loading and fuel property characteristics (Cruz and Fernandes 2008) and finding the combination of those variables that best matches expected fire behavior. It is not possible, however, to create calibrated custom fuel models when FFE-FVS is used to dynamically predict future fuels. The calibration would need to be updated against expected fire behavior as the fuel characteristics change in the simulation. It may be possible instead to use a partial calibration

Table 4. Percentage of scenarios for which each fuel model combination is selected for each fire across all model scenarios. If a fuel model combination is not selected, it is left blank. GR refers to grass; GS, to grass-shrub; SH, to shrub; TL, to timber-litter; and SB, to slash-blowdown fuel type models. Fuel models never selected in the study. These combinations do not reflect weightings assigned to each fuel model within the combination for a given scenario.

		GR2	GS2	SH1	SH2	TL6	TL9	SB2
Stickpin	GS1	72.5	0.5	23.3				
	GS2			2.1				
	TL5					1.1		
	SB2					0.5		
King	GS2			11.7	2.5			
	SB2					72.1		
	SB3						4.1	9.5

that provides plausible values of fuel characteristics while fixing the fuel load (Burgan 1987). These calibrated characteristics could then be used in conjunction with model-predicted fuel loadings in a custom fuel model to predict fire behavior. This is an area for future research. There have also been efforts to update the Rothermel (1972) model to use measured fuels in the Fuels Characteristic and Classification system (Sandberg et al. 2007), but this has not been evaluated against observed fire behavior.

We found that FFE-FVS predictions of fire behavior were sensitive to parameters that modify fine woody fuel loading, but not those that modify coarse woody fuel loadings (Figure 2). Models differ in whether smoldering combustion of coarse woody fuels is included to predict fire behavior. For example, the Rothermel (1972) model used by FFE-FVS to calculate fire behavior only includes smaller fuels in the flaming phase of combustion. The Van Wagner (1977) model of crown fire initiation uses Byram's (1959) intensity calculation that includes the contribution of smoldering combustion of coarse woody fuels. In models like FFE-FVS, Rothermel's and Van Wagner's models are often inappropriately combined in a way that underpredicts fire behavior metrics (Cruz and Alexander 2010, Schoennagel et al. 2012) such as surface fireline intensity and crown fire initiation. They do not account for the potential contribution of coarse woody fuels to the intensity and spread of large fires (Brown et al. 2003). High snag density and associated woody fuel accumulation can increase a wildfire's "resistance to control" (Page et al. 2013). Process-based models such as BURNUP (Albini and Reinhardt 1995, 1997) or physics-based models (Mell et al. 2007) may produce more robust predictions of intensity (Nemens et al. 2019). The more complex structures of process-based models, however, have additional uncertainty associated with increased data requirements and model structure (Kennedy et al. 2020). Their use requires substantial efforts in model assessment (Alexander and Cruz 2013) and to align fuel characterization with model requirements (Keane 2013).

Although this analysis was conducted for a limited ecological context and with one model, the sensitivities uncovered here would likely be present in similar models of forest stand and fuel dynamics. The basic structures that account for fuel accumulation (mortality and snag fall) and fuel loss (disturbance and decomposition) would be similar in such models. Fire behavior predictions would depend on available fuel models that may differ in different systems, but the limitations of such models would still apply.

Conclusions and Recommendations

A sensitivity analysis is an interrogation of model uncertainty that helps to identify model parameters that have more influence on predictions. In the interpretation of a sensitivity analysis, we may illuminate unanticipated model behavior and parameter interactions. However, a sensitivity analysis is not a model validation, which requires comparison of model predictions to observed data. In the sensitivity analysis presented here, we do not have data on fuel succession and future fire behavior to which predictions can be compared, so we cannot inform the adequacy of the model to predict fuel succession and fire behavior. Rather, we can point to areas where further research is warranted and where there may be potential model improvements.

To perform a sensitivity analysis, it is best practice to evaluate plausible ranges of parameter and input data values, such as a 95 percent confidence interval of an empirically estimated parameter value. The region- and species-specific default values for the snag fall and surface fuel decomposition rates that are used in FFE-FVS have been estimated empirically and are thereby point estimates with associated sampling and measurement errors. We were unable to identify in the FFE-FVS manual and guides plausible error bounds on the point estimates, which led us to use a simple factorial design that applied a multiplier to the default value. It may be that uncertainty in the default parameter is actually lower or higher than that represented here. To better understand the consequence of the high sensitivity to the snag fall and surface fuel decomposition rates, standard errors on these (and other empirically estimated parameters) should be reported along with their default point estimates. When uncertainty in the parameter estimates is quantified, these can be used to generate plausible intervals for important model outputs (Kennedy et al. 2020).

Below we give some general conclusions for model users who choose to use FFE-FVS, or a similar model, to predict fuel succession and future fire behavior:

1. Carefully consider parameters that control snag fall and surface fuel decomposition rates. Absent site-specific information, evaluate multiple rates to approximate uncertainty in predicted postdisturbance fuel accumulations.
2. Be thoughtful of choosing between stylized fuel models and modeled fuel values and carefully consider fuel characteristics in the context of expected fire behavior.
3. More structured assessment of model predictions against empirical measurements is required to credibly inform choice of model settings.
4. Initial snag density is important and should be measured carefully in a study that predicts postdisturbance fuel accumulations. These measurements may be improved by remote sensing techniques such as airborne lidar to map snag density (Wing et al. 2015).

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Supplementary Figures.

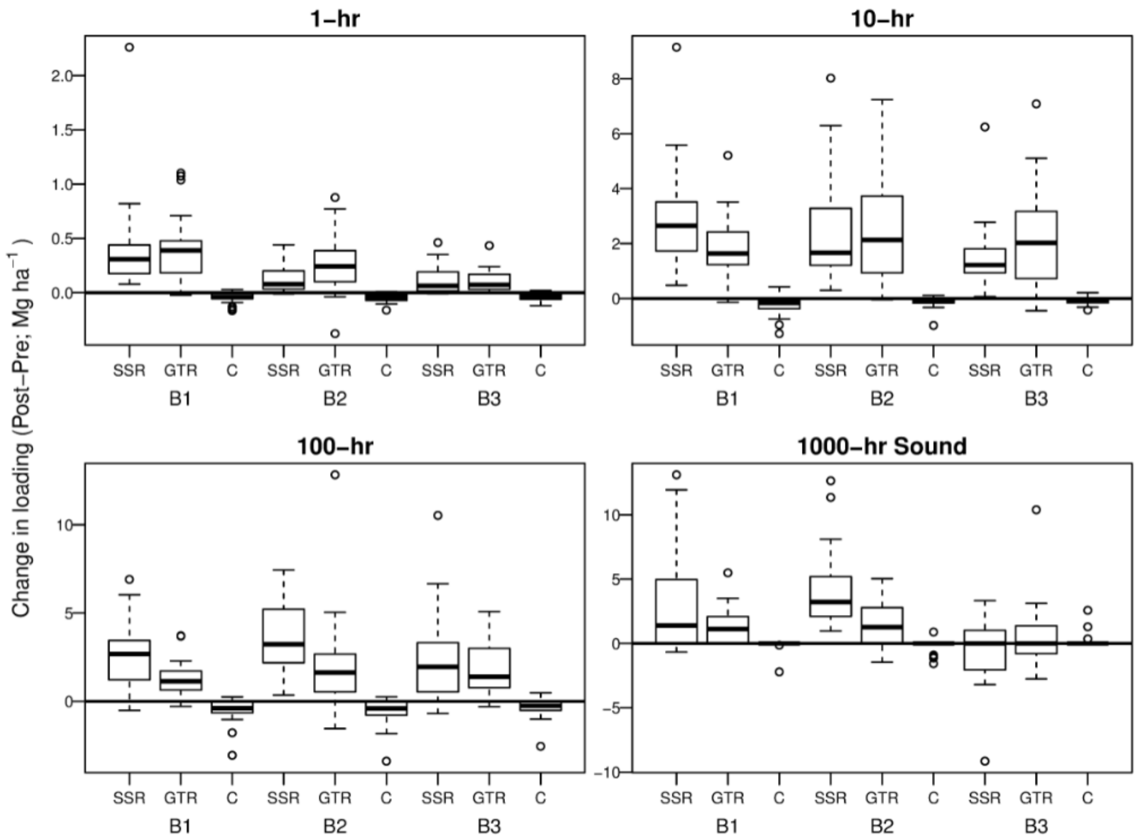

Figure S1. Distribution of observed change in loading (post-pre treatment) across all plots within each treatment x block combination.

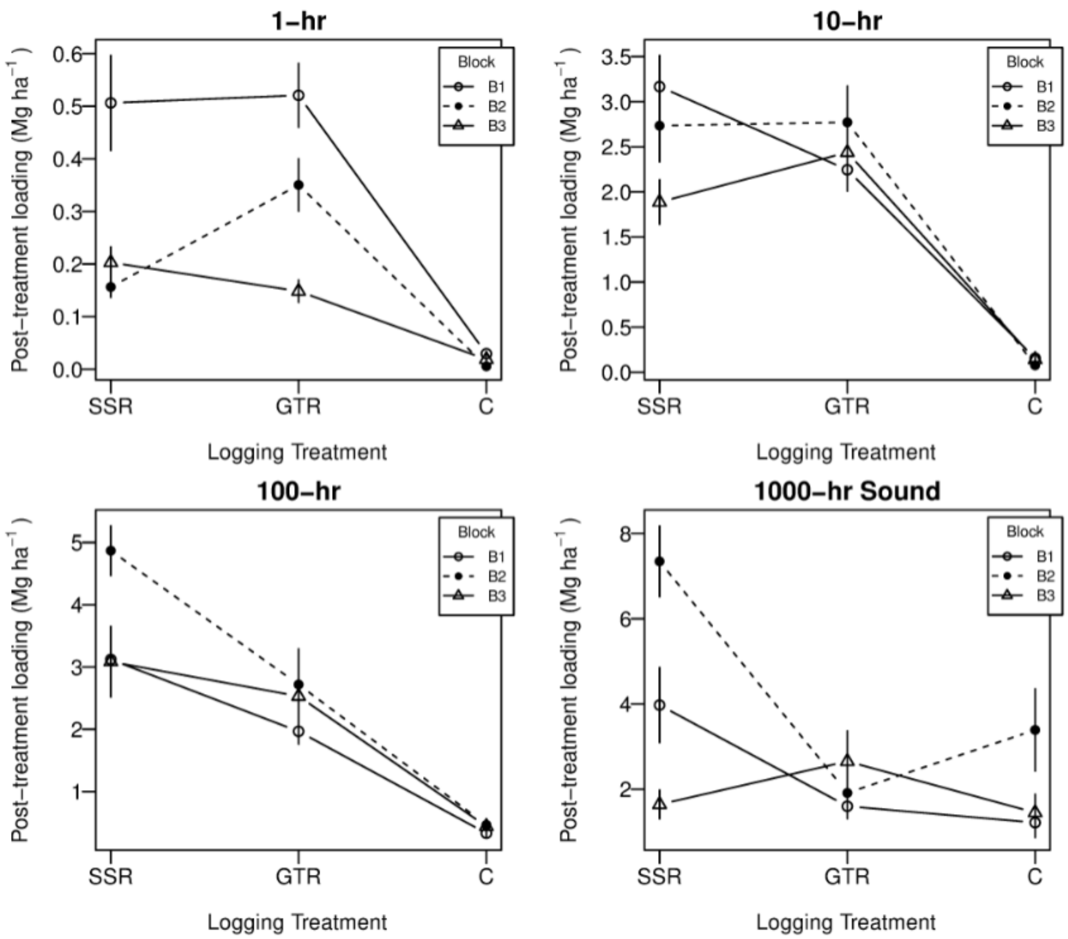

Fig. S2. Mean post-treatment loading, by treatment and block. Vertical lines indicate +/- 1 standard error.

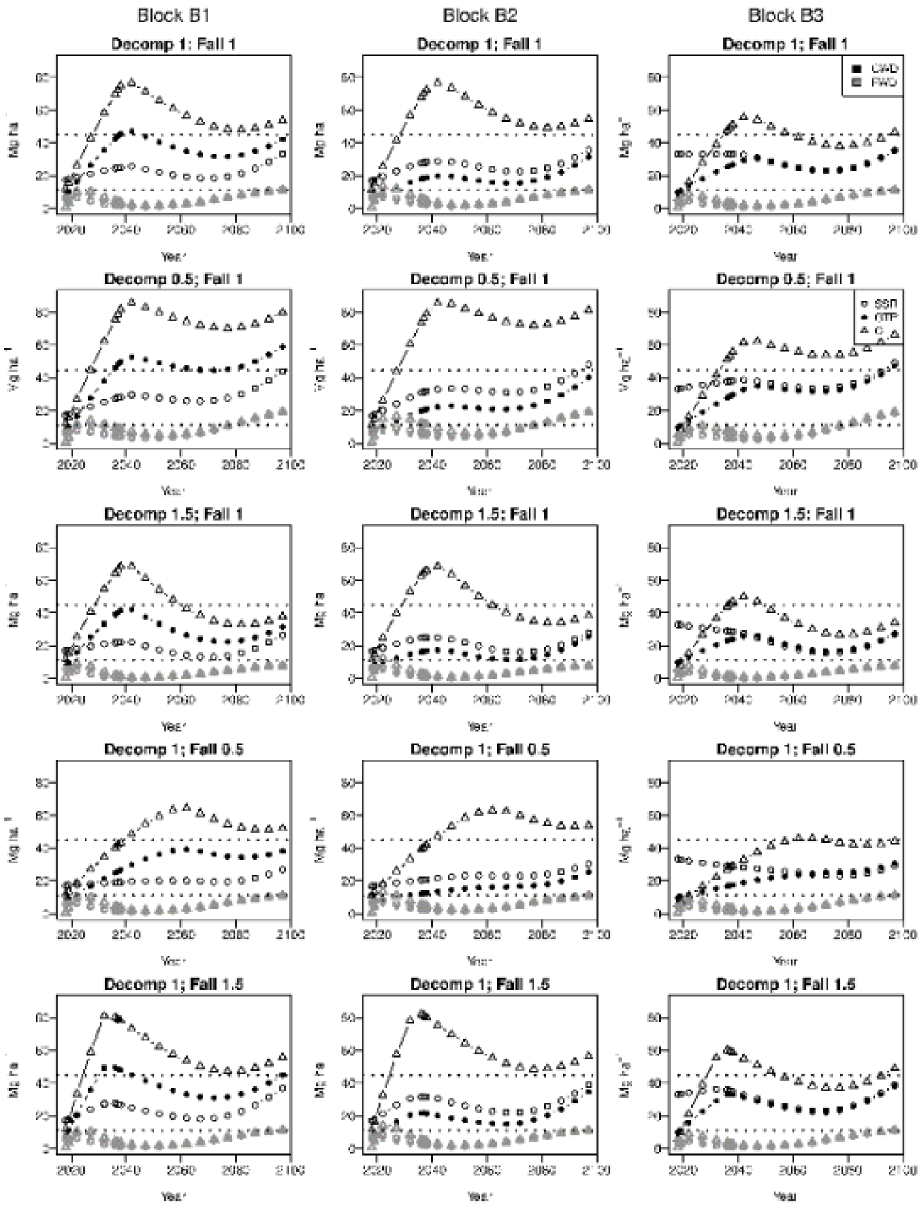

Figure S3. Coarse and fine woody fuel over time predicted by FFE-FVS for different values of surface fuel decomposition (Decomp) and snag fall (Fall) rate. The values given are multipliers of the default value (e.g., a value of 0.5 scales the corresponding parameter to 0.5 times its default value). Timing and magnitude of peak fuels differ among the parameter settings, but the comparisons among the treatments do not. CWD loadings were simulated with no reburn wildfire to understand parameter values on fuel succession without confounding reburn effects.