

1 Balancing uncertainty and complexity to incorporate fire-spread in an eco-hydrological model

2 Running head: Fire spread and eco-hydrology

3 Maureen C Kennedy (corresponding author)

4 University of Washington, School of Environmental and Forest Sciences

5 Current address: University of Washington, School of Interdisciplinary Arts and

6 Sciences, 1900 Commerce St, Box 358436, Tacoma, WA, 98402

7 mkenn@uw.edu

8 Donald McKenzie.

9 Pacific Wildland Fire Sciences Laboratory, Pacific Northwest Research Station, US

10 Forest Service, Seattle, WA

11 Christina Tague, Aubrey L Dugger.

12 University of California, Santa Barbara, Bren School of Environmental Science and

13 Management

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16 **Abstract**

17 Wildfire affects the ecosystem services of watersheds, and climate change will modify  
18 fire regimes and watershed dynamics. In many eco-hydrological simulations fire is included as  
19 an exogenous force. Rarely are the bi-directional feedbacks between watersheds and fire regimes  
20 integrated in a simulation system because the eco-hydrological model predicts variables that are  
21 incompatible with the requirements of fire models. WMFire is a fire-spread model of  
22 intermediate complexity designed to be integrated with the Regional Hydro-ecological  
23 Simulation System (RHESSys). Spread in WMFire is based on four variables that a) represent  
24 known influences on fire spread: litter load, relative moisture deficit, wind direction, and  
25 topographic slope, and b) are derived directly from RHESSys outputs. The probability that a fire  
26 spreads from pixel to pixel depends on these variables as predicted by RHESSys. We tested a  
27 partial integration between WMFire and RHESSys on the Santa Fe (New Mexico) and the HJ  
28 Andrews (Oregon State) watersheds. Model assessment showed correspondence between  
29 expected spatial patterns of spread and seasonality in both watersheds. These results demonstrate  
30 the efficacy of an approach to link eco-hydrologic model outputs with a fire spread model.  
31 Future work will develop a fire effects module in RHESSys, for a fully-coupled, bi-directional  
32 model.

33

34 **Brief Summary:** Fire spread is integrated with an eco-hydrological model designed to predict  
35 physical and biological watershed dynamics. The challenges of matching the requirements of  
36 predicting fire spread with the outputs of a model not designed for fire are evaluated and  
37 overcome in model design.

## 38 **Introduction**

39 Wildfire affects both the structure and function of watersheds, including rock weathering,  
40 modifications to vegetation, microbial and faunal activity, and changes to the soil that affect  
41 hydrological processes (Shakesby and Doerr 2006; Hyde *et al.* 2013). In turn, the spatial and  
42 temporal patterns of fuels and moisture in a watershed modify fire regimes. These multi-  
43 directional influences necessitate the dynamic integration of fire and eco-hydrological modeling,  
44 in order to project future watershed processes adequately.

45 Eco-hydrological models forecast watershed processes and water resources under  
46 changing climates and management (Tague and Dugger 2010; Fatichi *et al.* 2016) by combining  
47 physical hydrological processes with biological dynamics (Hannah *et al.* 2004; Wood *et al.*  
48 2007). However, disturbance regimes are rarely linked dynamically to eco-hydrological  
49 projections, and eco-hydrological models often ignore disturbance events (Hannah *et al.* 2007).  
50 This is problematic, especially for projections of future dynamics, because fires are predicted to  
51 become more extensive and severe in many regions (Flannigan *et al.* 2009; Littell *et al.* 2010;  
52 Stavros *et al.* 2014). This presents an increasing risk to natural resources, property, and  
53 ecosystem services (Hurteau *et al.* 2014; Rocca *et al.* 2014).

54 It is a challenge to integrate a model of fire with an established eco-hydrological model.  
55 Eco-hydrological models are not designed from the outset to quantify biomass in a manner  
56 compatible with the requirements of the most-used fire models. For example the Regional  
57 Hydro-Ecological Simulation System (RHESSys) is an eco-hydrology model that has been  
58 applied widely in forested watersheds to estimate streamflow, forest productivity, and mortality  
59 risk (Tague and Band 2004; Zierl *et al.* 2007; Tague, Choate, *et al.* 2013; Tague, McDowell, *et*  
60 *al.* 2013; López-Moreno *et al.* 2014). Processes in RHESSys are spatially nested (Figure 1), and

61 patches are the smallest unit of spatial aggregation. Patches aggregate soil-moisture and land-  
62 cover characteristics. Within a patch, there may be canopy strata (vertical layers of biomass that  
63 aggregate processes such as photosynthesis and respiration); within these strata individual  
64 organisms (e.g., trees and shrubs) are not simulated. In RHESSys, as in many ecosystem carbon  
65 cycling models (Fatichi *et al.* 2016), biomass components such as leaves and stems are simulated  
66 en masse, in pools of carbon. This is also true for the litter layer below the canopy strata, which  
67 receives input of biomass from the overlaying canopy layers within a patch. The goal of  
68 RHESSys, and other similar models of biogeochemical cycling and eco-hydrology, is to simulate  
69 ecosystem processes rather than demographics, succession, or competitive interactions (Tague  
70 and Band 2004).

71         If we compare the variables used to describe biomass in RHESSys to the requirements of  
72 structurally complex fire models we see that there is an incompatibility (Figure 1). For example,  
73 semi-empirical models of fire spread that use Rothermel (1972) equations (e.g., Finney 2004)  
74 require specific characteristics of the fuelbed, usually represented by stylized fuel models (Scott  
75 and Burgan 2005). Fuel models quantify fuel loading and arrangement by size classes of dead  
76 fuels (e.g., litter, and 1-hr, 10-hr, 100-hr time lags), live non-woody and woody (herbs, grasses,  
77 shrubs), and spatial properties (surface area to volume ratio, fuel bed depth, packing ratio).  
78 Because RHESSys does not quantify these fire-relevant properties of biomass, reconciling the  
79 mismatch in relevant variables between fire models and eco-hydrological models is not trivial.  
80 There are two strategies to couple fire-spread with eco-hydrology (Figure 1): integrate a  
81 structurally complex fire model with an adapted eco-hydrological model, or design a fire model  
82 of intermediate complexity to integrate with the existing eco-hydrological model.

83 Integrating a structurally complex fire spread model with the eco-hydrological model  
84 requires modifying the eco-hydrological model to predict fire-compatible detailed accountings of  
85 fuel loading and arrangement. This has the advantage of increasing physical realism and  
86 reducing prediction uncertainty associated with fire spread, if the eco-hydrological model can  
87 simulate the detailed fuels accurately. However, detailed descriptions of fuels aren't required to  
88 simulate hydrological or ecophysiological processes (such as photosynthesis and  
89 evapotranspiration), which are the primary objectives of the eco-hydrological model. The  
90 outcome of this strategy would be to force a major re-engineering of the eco-hydrological model,  
91 requiring substantial new data sources for calibration and parameterization, with associated  
92 uncertainty in model structure and parameter estimation as well as a substantial increase in  
93 computational resources. We believe that modifying the eco-hydrological model to match the  
94 requirements of an existing fire model would add uncertainty to the predictions of the fire-eco-  
95 hydrological model coupling. The cumulative effect of such uncertainty can be nonlinear; for  
96 example, a 10% error in parameter estimation can propagate to an order of magnitude greater  
97 error in prediction (O'Neill *et al.* 1980).

98 Furthermore, it is imperative to define the model application niche (the domain over  
99 which the model is expected to perform well, and the domain over which model application is  
100 not appropriate; Environmental Protection Agency 2009) and to match the level of model  
101 structural complexity to the extent and quality of input data (Jackson *et al.* 2000; McKenzie and  
102 Perera 2015). The application niche of RHESSys is to predict aggregate patterns in watershed  
103 dynamics at time scales of decades to centuries, and how those respond to changes in climate and  
104 management. The application niche of RHESSys is not to predict specific events at a given  
105 location or time (e.g., timing and location of peak flows following a particular fire). It is

106 therefore sensible that RHESSys does not quantify the specific inputs required by a structurally  
107 complex model of fire spread, with an application niche including both the prediction of  
108 individual fire events and landscape-level burn probabilities. It is more appropriate to design a  
109 fire model of intermediate complexity that better matches the application niche of RHESSys and  
110 utilizes the existing RHESSys representation of ecosystem and hydrologic variables. Such a  
111 model uses the variables of RHESSys to simulate fire in a way that predicts aggregate spatial and  
112 temporal patterns of fire spread across the watershed, over decades and centuries.

113         The model WMFire (Kennedy and McKenzie 2017) is designed to accept the inputs of  
114 the eco-hydrological model and use them to predict aggregate spatial patterns of fire spread,  
115 seasonality, and fire extent and frequency rather than the perimeters and timing of individual fire  
116 events. The target application niche of WMFire is to predict a plausible set of outcomes for how  
117 fire regimes and fire spread respond to the underlying template of topography, fuels, and  
118 moisture predicted by the eco-hydrological model. In this study we assess a partial coupling of  
119 RHESSys and WMFire with the goal to define the application niche of WMFire by elucidating  
120 the fire regime characteristics that are predicted adequately and the fire regime characteristics  
121 that are not predicted adequately.

#### 122 *WMFire model assessment*

123         Model assessment is an iterative process (Reynolds and Ford 1999), and in our ongoing  
124 work we are assessing WMFire in three stages. At each stage we adapt the approach of  
125 Hornberger and Cosby (1985), where traditional statistical analyses of model fit to data are not  
126 feasible. The data on historical fire regimes are relatively sparse, with regimes assigned coarse  
127 characteristics such as seasonality, severity, frequency, and spatial patterns of fire size and  
128 spread. We are assessing WMFire against historical fire regimes, absent human interference, so

129 recent databases of fire occurrence are not applicable. In the approach of Hornberger and Cosby  
130 (1985) parameter values are identified that produce model results that are considered adequate  
131 according to some criterion (“behavioral” in the Hornberger and Cosby (1985) parlance).  
132 Uncertainty in parameter values is thereby characterized by the distribution of parameter values  
133 able to satisfy the criterion.

134 In the first stage of WMFire assessment Kennedy and McKenzie (2017) identified  
135 parameter values that were considered adequate to replicate several aggregate spatial statistics of  
136 a recent wildfire. In this analysis they discovered the parameter value associated with fuel  
137 moisture had high uncertainty, which led us to improve WMFire to its current version. In the  
138 second stage of model assessment (presented here) we evaluate a partial integration of WMFire  
139 with RHESSys to assess the ability of WMFire to use RHESSys model outputs to adequately  
140 satisfy several criteria associated with historical fire regimes for two watersheds (HJ Andrews  
141 watershed in Oregon, USA (HJA), and Santa Fe watershed in New Mexico, USA (SF); Figure  
142 2). This stage of model assessment does not incorporate fire effects for two main reasons. The  
143 fire effects module for RHESSys is still under development, and in this second stage of  
144 assessment we want to isolate the uncertainties associated with the fire spread model before  
145 assessing the full integration with RHESSys including fire effects (to be completed in the third  
146 stage of model assessment). Through each stage of model assessment we are able to characterize  
147 the application niche of the model integration.

## 148 **Methods**

### 149 *Study sites description*

150 The upper Santa Fe River watershed (SF; Table 1) is the water supply catchment for  
151 Santa Fe, New Mexico. It is a steep, largely forested watershed with elevations ranging from

152 2300 to 3800m. Dominant vegetation is ponderosa pine at lower elevations (hereafter PP), mixed  
153 conifer (Douglas-fir, ponderosa pine, white pine, quaking aspen; hereafter MC) at mid  
154 elevations, and spruce-fir (Engelmann spruce dominant) at higher elevations. Mean annual  
155 precipitation is approximately 700 mm/year (at the mid-elevation Elk Cabin SNOTEL station),  
156 including summer monsoonal rainfall input and winter snowfall. The HJ Andrews watershed  
157 (HJA; Table 1) is located in the Western Oregon Cascade Range. Elevation ranges from 430 m-  
158 1600 m. The watershed is a mixed-conifer forest dominated by Douglas-fir and western  
159 hemlock. Mean annual precipitation is 2200 mm/year and falls primarily during the winter  
160 months, largely as rain at the lowest elevations and snow at the highest elevations.

#### 161 *RHESSys study site calibrations*

162 As with most watershed scale hydrologic models, in RHESSys subsurface drainage  
163 parameters usually need to be calibrated by comparison of modeled with observed streamflow  
164 using observed historical weather and climate data (Tague, Choate, *et al.* 2013; Garcia and  
165 Tague 2015). The implementation and calibration of RHESSys for SF has not been previously  
166 published; this calibration is described in supplementary material (S1). The implementation and  
167 calibration of RHESSys for HJA used in this study is described in Garcia *et al.* (2013), and  
168 summarized in supplementary material (S1).

#### 169 *Historical fire regime characteristics at each site*

170 We use published fire history data and the LANDFIRE fire regime group geospatial layer  
171 (LANDFIRE 2014; Supplementary S1) to characterize observed patterns in fire regime  
172 characteristics for each watershed. LANDFIRE is a project of multiple US federal agencies to  
173 produce data layers of landscape vegetation, fuels, and fire regimes. In SF Margolis and Balmat  
174 (2009) report mean fire return intervals between 4.3-31.6 years (Table 1) depending on how

175 many scars are used to indicate a fire and whether the fire is recorded in the PP or MC zone  
176 (Margolis and Balmat 2009). Among the fire scars for which season could be determined, most  
177 were in the beginning of the growing season (May-June). In the higher elevation spruce forest  
178 they found evidence for one stand replacing fire in 1685. Therefore a fire event in that portion of  
179 the watershed would not necessarily be expected over the simulation period. These patterns are  
180 corroborated by the LANDFIRE fire regime group data layer (see Figure S2), where there is a  
181 low-mixed severity fire regime inferred for the lower to middle watershed with mean fire return  
182 intervals  $\leq 35$  years, or 35-200 years depending on location (Figure S2; Table S2). LANDFIRE  
183 also predicts stand replacement fire severity in the upper SF watershed.

184 For HJA fire history studies and LANDFIRE document a mixed- or high-severity fire  
185 regime, with few small fires and the occasional large stand-replacing fire (Teensma 1987;  
186 Weisberg 1998; LANDFIRE 2014). The fire-return interval is on the order of decades to  
187 centuries, with a natural fire rotation ranging from approximately 50 years to approximately 200  
188 years (Table 1; Figure S1; Table S2). Therefore over the period for the simulation (50 years) we  
189 would expect at most one large fire for a single realization, regardless of whether fire effects are  
190 included in the model simulation. In mixed-severity fire regimes such as HJA fires more likely  
191 occur later in the growing season, as the fuels dry throughout the summer (Bartlein *et al.* 2008).

192 The documented fire history and LANDFIRE fire regime groups determine assessment  
193 criteria for this stage of WMFire assessment. For SF the criteria are (Table 1):

194 SF1. Spatial gradient in fire size and occurrence from the lower to upper watershed

195 SF2. Fire spread peaks in May-July

196 SF3. Fire-return interval 4.3-31.6 years

197 For HJA the criteria are (Table 1):

198 HJA1. No spatial gradient in fire size and occurrence

199 HJA2. Fire spread peaks in July-September

200 HJA3. Natural fire rotation 50-200 years.

201 *WMFire-RHESSys description*

202 Each month RHESSys calculates the monthly mean for litter carbon ( $\text{kg}\cdot\text{m}^{-2}$ ), and actual  
203 and potential evapotranspiration (ET and PET, respectively;  $\text{mm}\cdot\text{m}^{-2}\cdot\text{day}^{-1}$ ; Stephenson 1998),  
204 then passes those values as well as the digital elevation model to WMFire (Figure 3). (Note,  
205 RHESSys computes these values daily but we aggregate to a monthly time step as a compromise  
206 between allowing for sub-monthly changes in fire season, and the computational burden of  
207 running WMFire). Details on RHESSys estimates of litter carbon, ET, and PET can be found in  
208 Tague and Band (2004). As a surrogate for fuel moisture WMFire calculates the relative  
209 moisture deficit,  $1-\text{ET}/\text{PET}$  (Swann *et al.* 2012; Kennedy McKenzie 2017). Given that our goal  
210 is to predict plausible futures rather than specific events, and that fire is driven by stochastic  
211 processes such as weather events, we designed WMFire to be a stochastic model that subsumes  
212 in the probability calculation the uncertainty associated with the natural variability in fire events.  
213 When WMFire is called the following sequence of events occurs (Figure 3), described in more  
214 detail below:

- 215 1. Draw a random number of ignition sources. If this number is greater than 0, locate  
216 each ignition source randomly on the landscape.
- 217 2. For each ignition source located randomly on the landscape, test the chosen pixels for  
218 fire start based on the fuel and moisture conditions of the pixel.
- 219 3. For each successful fire start simulate fire spread based on the fuel, moisture,  
220 topographic, and wind conditions.

221 4. Return to RHESSys which pixels, if any, were burned during the simulation.

### 222 1. Ignition sources

223 A successful fire ignition occurs when two events happen in sequence: first there is an  
224 ignition source located on a landscape (such as lightning, a campfire, etc.), then that ignition  
225 source successfully ignites a wildfire. While the instance of an ignition source that successfully  
226 starts a wildfire is observable, observations of ignitions that do not lead to wildfires are severely  
227 limited. Thus, the full sample space of ignition source rates, those that both do and do not result  
228 in a wildfire, is essentially unobservable. Adherence of ignition source rate to a particular  
229 historical frequency of ignition sources (for which there are few reliable data sources) introduces  
230 false precision into simulations and ignores the high uncertainty in determining ignition sources  
231 on a landscape. Even if ignition rates are known they are poor predictors of area burned at almost  
232 any scale (Krause *et al.* 2014; Faivre *et al.* 2016).

233 In WMFire, we compute a successful fire ignition as a function of the ignition source rate  
234 and the probability that a given ignition leads to a fire. The latter variable is a function of  
235 landscape and climatic variables that can be readily computed by RHESSys (described in detail  
236 below). As noted above, the lack of observable data limits the development of predictive models  
237 of ignition source rates. Given this uncertainty, for WMFire we assume a simple mean rate of  
238 ignition sources ( $\lambda$ ), informed by the area of the watershed (a larger watershed is given a larger  
239 ignition source rate). The number of ignition sources to be tested for fire start is drawn from a  
240 Poisson distribution, with the ignition source rate as the Poisson rate parameter. Given that data  
241 are not available for the ignition source rate we conduct a local sensitivity analysis on the mean  
242 ignition source rate for each watershed (0.10, 0.25, and 0.5 mean ignition sources per month for  
243 HJA, and 1, 1.5, and 2 mean ignition sources per month for the larger SF watershed; Table 2).

244 2. Test for fire start

245 A random pixel in the watershed is chosen for each ignition source to test for successful  
246 fire start. In WMFire the probability of a successful ignition ( $p_i$ ), given the presence of an  
247 ignition source, depends on the RHESSys predicted values of litter load (l), and relative deficit  
248 (d). First individual probabilities are calculated associated with each variable ( $p_i(l)$ ,  $p_i(d)$ ;  
249 described below), then the final probability of successful ignition is the product of the  
250 component probabilities:

$$251 \quad p_i(l,d) = p_i(l)*p_i(d) \quad (1)$$

252 3. Fire spread given successful fire start

253 The spread model in WMFire is based on a system of dynamic percolation (Caldarelli *et*  
254 *al.* 2001; Kennedy and McKenzie 2010; McKenzie and Kennedy 2012). The basic sequence of  
255 fire spread is (Figure 3): if an ignition source successfully ignites a pixel, then WMFire tests the  
256 orthogonal neighbors of that pixel against the probability of spread ( $p_s$ ), independently. For each  
257 pixel to which spread is successful, spread to each of its neighbors is tested in the next iteration.  
258 Previously burned pixels can no longer spread fire.

259 In WMFire the value of  $p_s$  is determined by the RHESSys-predicted value of litter load  
260 (l), relative deficit (d), topographic slope (S) and the orientation of spread relative to wind  
261 direction (w). A probability associated with each of those components is calculated ( $p_s(l)$ ,  $p_s(d)$ ,  
262  $p_s(S)$  and  $p_s(w)$  for the probability of spread associated with fuel load, deficit, slope, and wind,  
263 respectively). The final probability of spread ( $p_s(l,d,S,w)$ ) is calculated as the product of the  
264 component probabilities:

$$265 \quad p_s(l,d,S,w) = p_s(l)p_s(d)p_s(w)p_s(S) \quad (2)$$

266 In this formulation, if any of the components predicts a probability of zero for spread (is a barrier  
 267 to spread), then spread cannot happen. Conversely, if all components predict a probability of 1  
 268 for spread (no barriers to spread), then spread will happen. Next we describe how each  
 269 component probability for fire start and fire spread are calculated.

270 *Litter load and relative deficit*

271 We assume that the probability associated with litter load and relative deficit increases  
 272 with increasing values of each of those, and this relationship takes a sigmoid shape. The function  
 273 that associates  $p_s$  and  $p_i$  with litter load ( $l$ ) and relative deficit ( $d$ ) takes the form:

274 
$$p_s(l) = \frac{1}{1+e^{-k_1 l(l-k_2 l)}}; \quad (3)$$

275 
$$p_s(d) = \frac{1}{1+e^{-k_1 d(d-k_2 d)}} \quad (4)$$

276  $k_1$  defines the shape of the curve (its steepness),  $k_2$  defines where along the x-axis the function  
 277 crosses a value of 0.5 (Figure 4a,b; Table 2), which is near the value of the percolation threshold  
 278 estimated for this kind of dynamic percolation (Kennedy and McKenzie 2010).

279 *Wind*

280 We assume that the probability of fire spread is highest in the wind direction, then  
 281 decreases as the angle of spread deviates from the wind direction. We adapt a trigonometric  
 282 function used by Weisberg *et al.* (2008):

283 
$$p_s(w) = k_{1\_wind} (1 + \cos(\gamma - \omega)) + k_{2\_wind}, \quad (5)$$

284 where  $k_{1\_wind}$  controls the reduction of  $p_s(w)$  as the angle of spread deviates from the wind  
 285 direction,  $\omega$  is the wind direction (rad),  $\gamma$  is the orientation of the neighbor pixel relative to the  
 286 pixel spreading fire (rad) and  $k_{2\_wind}$  is the probability of spread against the direction of the wind  
 287 (Figure 4c; Table 2). This function can take values  $>1.0$ , in which case  $p_s(w)$  is set to 1. The  
 288 empirical modeling of wind distributions is described in supplementary material.

289 *Slope*

290 The probability of fire spread increases uphill and decreases downhill from the source  
291 pixel. We adapt our curve from the model LANDSUM (Keane *et al.* 2002):

$$292 \quad p_s(S) = k_{1\_slope} e^{I k_{2\_slope} S^2}, \quad (7)$$

293 where  $k_{1\_slope}$  gives the value of  $p_s$  at zero slope,  $k_{2\_slope}$  defines the steepness of the curve, and  
294  $I=1$  if  $S>0$ ,  $-1$  otherwise (Figure 4d; Table 2). This function can take values  $>1.0$ , in which case  
295  $p_s(S)$  is set to 1. The slope relative to the direction of fire spread is calculated from the digital  
296 elevation model.

297 *WMFire parameter values*

298 The values of the eight WMFire parameters were selected by continuing the first  
299 assessment procedure described by Kennedy and McKenzie (2017), and the chosen values are  
300 given in Table 2. Note that the parameter values for  $p_i(l)$  and  $p_i(d)$  are the same as those for  $p_s(l)$   
301 and  $p_s(d)$ .

302 *Assessing WMFire against criteria*

303 To assess the fire spread model we generate RHESSys-predicted grids of mean monthly  
304 fuel load and mean monthly relative deficit over the historical period for each watershed. These  
305 are used as a time series of input grids for WMFire, along with the DEM and the empirical wind  
306 distributions (Figure 3). We conducted 500 Monte Carlo (MC) replicate simulations for each  
307 time series of deficit and load resulting in 300,000 total WMFire calls for HJA and 396,000 for  
308 SF. For all fire regime characteristics we count fire spread both at a threshold of successful  
309 ignition ( $>0$  ha burned) and at a threshold of minimum successful spread ( $>100$  ha burned). We  
310 chose the first threshold to represent any successful start, then the second threshold to represent  
311 successful spread given fire start. The 100 ha threshold is relatively arbitrary, but we believe

312 sufficient for the purpose of comparing simulations to fire history data, where fire size is difficult  
313 to determine.

314 To assess the spatial distribution of fire spread (criterion 1 for each watershed) we  
315 determine pixel-level probabilities of fire activity by calculating, for each month, the proportion  
316 of times an individual pixel experiences fire across replicate simulations. We then create maps of  
317 those probabilities and compare the patterns to the criterion for each watershed (Table 1).

318 To assess the seasonality of fires in the regime (criterion 2 for each watershed) we  
319 calculate the proportion of replicates that experience fire (>0 ha burned, or >100 ha burned) each  
320 month through all simulation years. We then compare the maximum month of fire occurrence to  
321 the criterion for each watershed (Table 1). We also record fire sizes to characterize the simulated  
322 fire size distribution.

323 To compare against the third criterion for each watershed we calculate the fire-return  
324 interval the mean number of years between fires (> 0 ha burned and >100 ha burned) for each  
325 replicate simulation. The natural fire rotation (NFR; Heinselman 1973) is also calculated for each  
326 replicate.

$$327 \quad NFR = \frac{A_s}{\bar{A}}, \quad (8)$$

328 where  $A_s$  is the total area of the watershed, and  $\bar{A}$  is the mean annual area burned throughout the  
329 individual time series (Swetnam *et al.* 2011). We then compare the distributions of fire return  
330 interval and NFR to the criterion for each watershed (Table 1).

## 331 **Results**

332 Empirical wind distributions and RHESSys-predicted values of litter load and relative  
333 deficit for each watershed are given in supplementary material (S1; Table S1, Figures S3-S4).

334 Here we focus on comparing WMFire predictions to the assessment criteria for each watershed,  
335 which are derived from site-specific literature and LANDFIRE data, and are listed in Table 1.

336 *Criterion 1: Spatial distribution of fire spread*

337 Simulated pixel-wise probabilities of fire in SF increase from the lower to the middle  
338 watershed, then decline in the upper portion of the watershed (Figure 5), and this spatial pattern  
339 is not sensitive to the ignition source rate (Figures S8-S10). This spatial pattern satisfies criterion  
340 SF1 (Table 1). Simulated pixel-wise probabilities of fire in HJA do not show an obvious spatial  
341 gradient, although there is patchiness in fire probability (Figure 6). These spatial patterns are not  
342 sensitive to the ignition source rate (Figures S5-S7), and satisfy criterion HJA1.

343 *Criterion 2: Seasonality of fire occurrence*

344 For SF the proportion of replicates that achieve a fire size > 100 ha shows a distinct  
345 seasonality with a peak in June. All months show a small probability of fire activity, but most  
346 activity is in the months May – July (Figure 7). This pattern in seasonality of fire spread is not  
347 sensitive to the value of ignition source rate (Figures S8-S10), and it satisfies criterion SF2. The  
348 value of the proportion of successful fire is sensitive to the mean ignition source rate. WMFire  
349 predicts that fire activity for HJA increases as the growing season progresses, peaking in the late  
350 summer and early fall (Figure 7). In the HJA fire is predicted to be absent in the late winter and  
351 early spring months, and it rarely occurs in the late fall and early winter. This pattern in  
352 seasonality of fire spread is not sensitive to the value of ignition source rate (Figures S5-S7), and  
353 it satisfies criterion HJA2. The value of the proportion of successful fires in HJA is sensitive to  
354 ignition source rate, and it is near zero when the ignition source rate is 0.1 per month.

355 *Criterion 3: Fire return interval*

356 In both watersheds metrics of fire return are sensitive to the mean ignition source rate.  
357 For mean ignition source rates of 1, 1.5, and 2 per month, respectively, in SF the mean values of  
358 NFR are 84.3, 54.5, and 40.9 years; the mean return interval for successful ignition is 1 year for  
359 all mean ignition source rates; the mean return intervals for fires that achieve a size at least 100  
360 ha are 9.1, 6.5, and 5.2 years (Figure 8). For all tested mean ignition source rates criterion SF3 is  
361 satisfied. For mean ignition source rates of 0.1, 0.25, and 0.5 per month, respectively, in the  
362 smaller HJA watershed the mean values of NFR are 314431.9, 9.9, and 4.6 years; the return  
363 intervals for successful ignition are 13.6, 1.4, and 1.1 years; the mean values for return intervals  
364 for fires > 100 ha are 19.3, 4.4, and 2.5 years (Figure 8). The closest match between model  
365 prediction and criterion HJ3 is for a mean ignition source rate of 0.1 per month.

#### 366 *Fire size distribution*

367 For fires that achieve at least 100 ha the distributions of fire sizes are right-skewed  
368 (Figure 8) in SF. The largest fires occur in the early summer fire season. The fire-size  
369 distribution in HJA is relatively symmetric. Maximum fire sizes are slightly larger in HJA than  
370 in SF, with more fires achieving the larger fire sizes (Figure 8).

#### 371 **Discussion**

372 By matching the level of complexity and application niche of RHESSys, WMFire is able  
373 satisfy the first two assessment criteria (spatial distribution of fire spread and seasonality of fire  
374 occurrence) when compared to documented fire histories for HJA and SF (Figures 5- 6; Table 1).  
375 The ability of WMFire to satisfy these two criteria is not dependent on the value of the ignition  
376 source rate (Figures S5-S10).

#### 377 *WMFire application niche*

378 For SF WMFire predicts a peak in fire spread during the late spring and early summer,  
379 which is expected given the fire history recorded for that watershed (Margolis and Balmat 2009;  
380 LANDFIRE 2014). For HJA WMFire predicts a peak in fire spread during the late summer, also  
381 consistent with the observations of fire history in that watershed (Teensma 1987; Weisberg 1998;  
382 LANDFIRE 2014). These observed patterns in historical seasonality are not sensitive to the  
383 value of ignition source rate, indicating that there is little uncertainty in the seasonality of fire  
384 spread predicted by WMFire.

385 For SF WMFire predicts a spatial gradient where the highest density of fire occurrence is  
386 in the middle portion of the watershed. This pattern matches the fire history data (Margolis and  
387 Balmat 2009) and LANDFIRE predictions (Figure S2; Table S2). LANDFIRE predicts that the  
388 lowest return intervals (and thereby the greatest expected fire occurrence) are in the lower to the  
389 middle portion of the watershed, and fire history data show that the middle portion of the  
390 watershed is expected to have a mixed-severity fire regime.

391 The simulated fire size distribution in SF is right-skewed and heavy-tailed (Figure 8),  
392 which follows other estimated empirical fire size distributions (Malamud *et al.* 2005). The  
393 simulated fire size distribution in HJA shows larger values and is more symmetric, implying that  
394 when a fire does burn in HJA it tends to be large, and smaller fire sizes are rare (Figure 8).  
395 LANDFIRE predicts a mixed to high severity fire regime for HJA, which is expected to have  
396 larger fires of higher severity than SF. For any individual fire simulated in HJA, the spread  
397 pattern follows what is expected in this fire regime—a relatively large fire supported by high  
398 relative deficits and fuel loading (Teensma 1987; Weisberg 1998; Fiorucci *et al.* 2008). This is  
399 consistent with WMFire predictions of fire size for HJA. The fire size distribution in both

400 watersheds is not sensitive to the ignition source rate, indicating that there is little uncertainty in  
401 the fire size distribution predicted by WMFire.

402         In this stage of model assessment we find that the outcomes of successful ignitions—  
403 fires that spread, their seasonality, and extent—are metrics of the fire regime for which our  
404 current model structure is adequate. However, sensitivity analysis of ignition source rate shows  
405 that the ability of WMFire to satisfy the third criterion for each watershed (fire frequency  
406 measured by return interval and natural fire rotation) is sensitive to the value of ignition source  
407 rate (Figure 8). Therefore some calibration of ignition source rates is necessary (as with some  
408 processes in the partner model RHESys) to ensure that fire frequency *per se* is in line with  
409 historical observations. Our procedure is one level of abstraction (McKenzie and Perera 2015)  
410 above trying to replicate specific historical realizations of this stochastic process, in that our  
411 application niche is to characterize plausible distributions of the future rather than individual  
412 outcomes. As such, we believe it to be more robust to future projections, the principal goal of  
413 RHESys/WMFire, than would be any attempt to model future changes in ignition rates.

#### 414 *WMFire prediction uncertainty*

415         The sensitivity of fire frequency to ignition source rate is non-linear, with the strongest  
416 sensitivity at lower values of mean ignition source rate. An ignition source rate of 0.10 ignitions  
417 per month predicts a natural fire rotation and fire return interval that match fire history data and  
418 LANDFIRE data for HJA (Figure 8), whereas WMFire is able to match fire history and  
419 LANDFIRE data for SF with multiple values of ignition source rate. For SF this results in a  
420 mean ignition test rate of 0.00013 to 0.00026 \*ha<sup>-1</sup>\*month<sup>-1</sup> and for HJA this results in a mean  
421 ignition test rate of 0.000016\*ha<sup>-1</sup>\*month<sup>-1</sup>. These values of mean ignition source rate do not  
422 scale consistently with watershed size, which indicates that there is some uncertainty in fire

423 occurrence that is not explained by WMFire when integrated with RHESSys absent fire effects.  
424 These rates per ha can help to narrow the calibration space when WMFire is applied to a new  
425 watershed in a similar vegetation type. To further calibrate the mean ignition source rate in a new  
426 watershed the RHESSys-WMFire model should be run with multiple ignition source rates  
427 commensurate with those found here, and the rate that adequately matches expected patterns of  
428 fire occurrence should be chosen.

#### 429 *Future WMFire development and assessment*

430 We designed WMFire to be a model of fire spread that balances model complexity with  
431 data input uncertainty. The model assessment presented here shows that with this balance the  
432 model is able to predict seasonality and spatial patterns of fire occurrence, with a documented  
433 uncertainty in model predictions of fire frequency that is associated with the mean ignition  
434 source rate.

435 The uncertainty in WMFire predictions of fire occurrence metrics such as fire return  
436 interval and natural fire rotation gives a pathway for improving the model integration. In  
437 WMFire fire frequency predictions are sensitive to the mean ignition source rate, and the lower  
438 ignition source rate required for HJA may represent limitations in our current approach for  
439 estimating successful fire ignitions and spread. One possible limitation may be insufficient  
440 resolution of canopy structure because the current version of WMFire utilizes a single integrated  
441 canopy in the estimation of deficit; however, in denser canopies, such as those in HJA,  
442 understory deficit may be more relevant to the probability of fire start than the total vegetation as  
443 modeled here. Future work will explore this possibility.

444 The absence of fire effects in RHESSys means that the integration of WMFire and  
445 RHESSys is not yet fully bi-directional, in that RHESSys dynamically modifies fire spread, but

446 the fire spread does not dynamically modify watershed characteristics. RHESSys is in the  
447 process of being updated to estimate fire effects. An important predictor of fire effects is the  
448 vertical stratification of the canopy fuels, with an understory canopy acting as ladder fuels to the  
449 upper canopy. The increased resolution of canopy structure that will be implemented for fire  
450 starts can also be used to estimate canopy-level fire effects. In our third stage of model  
451 assessment we will evaluate the improved simulation of fire starts with the fully-coupled fire  
452 effects model against detailed fire regime characteristics for several watersheds in the Western  
453 US. We then will determine the application niche of the fully bi-directional coupled eco-  
454 hydrological and fire spread model.

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459 results presented in this paper can be found at: <https://dx.doi.org/10.6084/m9.figshare.3203938>.  
460 Updated RHESSys code can be found at <https://github.com/RHESSys/RHESSys/wiki>. The  
461 authors declare no conflicts of interest.

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587

588 **Tables**

589 Table 1. Characteristics of the study sites including expected fire regimes. Area gives the area of  
 590 each watershed (ha). Expected fire regime characteristics for Santa Fe (SF) and HJ Andrews  
 591 (HJA) are based on published fire histories for each site.

	Area (ha)	elevation	annual precipitation	Criterion 1: Spatial gradient fire occurrence	Criterion 2: Seasonality of fire occurrence	Criterion 3: Fire frequency
SF	7559	2300 to 3800m	700 mm/year	Increasing from lower to middle watershed, then decreasing in lower watershed	May-July	4.3-31.6 years (fire return interval)
HJA	6175	430 m to 1600 m	2200 mm/year	No spatial gradient	August-September	50-200 years (natural fire rotation)

592

593 Table 2. WMFire parameter values and empirically estimated wind coefficients for both the  
 594 Santa Fe (SF) and HJ Andrews (HJA) watersheds.  $k_{1\_load}$  controls the steepness of the probability  
 595 of spread with increasing litter load,  $k_{2\_load}$  defines the litter load ( $kg \cdot m^{-2}$ ) at which the associated  
 596 probability of spread crosses a value of 0.5,  $k_{1\_def}$  controls the steepness of the probability of  
 597 spread with increasing relative deficit (1-ET/PET),  $k_{2\_def}$  defines the relative deficit at which the  
 598 associated probability of spread crosses a value of 0.5,  $k_{1\_wind}$  controls the wind direction at  
 599 which the associated probability falls below 1,  $k_{2\_wind}$  gives the associated probability of spread  
 600 against the wind direction,  $k_{1\_slope}$  gives the associated probability of spread on a flat slope,  
 601  $k_{2\_slope}$  controls the steepness of the probability of spread with increasing or decreasing slope.  $\lambda$  is  
 602 the mean ignition source rate (per month)

WMFire parameters	$k_{1\_load}$	$k_{2\_load}$	$k_{1\_def}$	$k_{2\_def}$	$k_{1\_wind}$	$k_{2\_wind}$	$k_{1\_slope}$	$k_{2\_slope}$	$\lambda$
SF & HJA	3.9	0.07	3.8	0.27	0.87	0.48	0.91	1.0	HJA: 0.1,0.25,0.5 SF: 1,1.5,2

603 **Figure Captions**

604 Figure 1. Rationale for a model of intermediate complexity in watershed-scale projections of the  
605 effects of climate change on ecosystems (RHESSys coupled with WMFire). A fire model of  
606 high complexity and physical realism introduces extra uncertainty and computational burden  
607 when integrated with existing eco-hydrological model, without increased accuracy (in fact,  
608 probably false precision) for longer-term projections. The multi-scale RHESSys outputs would  
609 have to be collapsed (across scales) and disaggregated (into fuel size classes and fine-scale fire  
610 weather) to be used with a structurally complex fire model. Stochastic semi-mechanistic  
611 modeling allows us to match the complexity of the fire module to RHESSys outputs and inputs,  
612 thereby minimizing uncertainty and focusing on fire-regime characteristics rather than individual  
613 fires.

614 Figure 2. Location of the two study sites, HJ Andrews in Oregon, and the Santa Fe Watershed in  
615 New Mexico, and topography and spatial distribution of litter fuel loads ( $\text{kg}\cdot\text{m}^{-2}$ ) predicted by  
616 RHESSys for each watershed, given as a pixel-wise mean value across all years in the  
617 simulation.

618 Figure 3. Flow diagram for WMFire fire spread.

619 Figure 4. Function shapes for WMFire at the chosen parameter values. (a) Fuel load; (b) relative  
620 moisture deficit; (c) wind direction relative to spread direction (d) slope relative to spread  
621 direction. Horizontal line at  $p_s = 0.5$ .

622 Figure 5. Proportion of replicates where model simulates fire in each pixel across all years,  
623 calculated as the proportion of times each pixel experiences fire relative to the number of  
624 ignitions tried (reps \* years) for HJA with an ignition rate of 0.5 per month. Note different scales  
625 for Figures 6 and 7.

626 Figure 6. Proportion of replicates where model simulates fire in each pixel across all years,  
627 calculated as the proportion of times each pixel experiences fire relative to the number of  
628 ignitions tried (reps \* years) for SF with an ignition rate of 2 per month. Note different scales for  
629 Figures 6 and 7.

630 Figure 7. Proportion of replicates with fire size > 100 ha each month. Sources of variability are  
631 years and replicates. (a-c) HJA ignition rates of 0.10, 0.25 and 0.5 per month. Peak fire activity is  
632 predicted in the late summer and early fall months. (d-f) SF ignition rates of 1, 1.5, and 2 per  
633 month. Peak fire activity is predicted in the late spring and early summer months.

634 Figure 8. Natural fire rotation, fire return intervals, and fire size distributions (for fires that  
635 achieve size > 100 ha) for (a-c) the HJA and (d-f) SF watersheds. Source of variability is  
636 replicates (one value calculated per replicate simulation). Note different y-axis scales between  
637 SF and HJA.

638