

Manuscript Details

Manuscript number	FORECO_2017_882
Title	Changing spatial patterns of stand-replacing fire in California conifer forests
Article type	Full Length Article

Abstract

Stand-replacing fire has profound ecological impacts in conifer forests, yet there is continued uncertainty over how best to describe the scale of stand-replacing effects within individual fires, and how these effects are changing over time. In forests where regeneration following stand-replacing fire depends on seed dispersal from surviving trees, the size and shape of stand-replacing patches are critical metrics that are difficult to describe and often overlooked. We used a novel, recently-developed metric that describes the amount of stand-replacing area within a given distance of a live-tree patch edge, in order to compare fires that may be otherwise similar in fire size or the percentage of stand-replacing effects. Specifically, we analyzed 477 fires in California pine, fir, and mixed-conifer forests between 1984 and 2015 and asked whether this metric, the stand-replacing decay coefficient (SDC), has changed over time, whether it is affected by fire management, and how it responds to extreme weather conditions at the time of the fire. Mean annual SDC became smaller over time (significantly so in the Sierra Nevada region), indicating that stand-replacing patches became larger and more regularly shaped. The decrease in SDC was particularly pronounced in the years since 2011. While SDC is correlated with percent high-severity, it is able to distinguish fires of comparable percent high-severity but different spatial pattern, with fires managed for suppression having smaller SDC than fires managed for resource benefit. Similarly, fires managed by the US Forest Service had smaller SDC than fires managed by the National Park Service. Fire weather also played an important role, with higher maximum temperatures generally associated with smaller SDC values. SDC is useful for comparing fires because it is associated with more conventional metrics such as percent high-severity, but also incorporates a measure of regeneration potential – distance to surviving trees at stand-replacement patch edges – which is a biological legacy that directly affects the resilience of forests to increasingly frequent and severe fire disturbances. We estimate that from 1984–2015, over 80,000 ha of forestland burned with stand-replacing effects greater than 120 m in from patch edges, denoting areas vulnerable to extended conifer forest loss due to dispersal limitation. Managing unplanned ignitions under less extreme weather conditions can achieve beneficial “fine-grained” effects of stand-replacing fire where regeneration limitation is less of a concern. Because SDC is a useful single metric to compare fires, we introduce a web application to calculate SDC for any high-severity spatial layer that may be of interest.

Keywords	California; high-severity; mixed-conifer forests; patch dynamics; stand-replacing; wildland fire
Corresponding Author	Jens Stevens
Order of Authors	Jens Stevens, Brandon Collins, Jay Miller, Malcolm North, Scott Stephens
Suggested reviewers	Nicholas Povak, Brian Harvey, Zachary Steel, Sean Parks

Submission Files Included in this PDF

File Name [File Type]

SDC Trends CL V2.docx [Cover Letter]

Response to Reviewers.docx [Response to Reviewers]

SDC Trends HL V2.docx [Highlights]

SDC Trends MS V2.docx [Manuscript File]

SDC Trends MS V2 Tracked Changes.docx [Supporting File]

SDC Trends APP.docx [Supporting File]

To view all the submission files, including those not included in the PDF, click on the manuscript title on your EVISE Homepage, then click 'Download zip file'.

UNIVERSITY OF CALIFORNIA, BERKELEY

BERKELEY • DAVIS • IRVINE • LOS ANGELES • MERCED • RIVERSIDE • SAN DIEGO • SAN FRANCISCO

DEPARTMENT OF
ENVIRONMENTAL SCIENCE, POLICY, AND MANAGEMENT
BERKELEY, CALIFORNIA 94720



SANTA BARBARA • SANTA CRUZ

Editors-in-Chief, Forest Ecology and Management
28 August 2017

To the Editors:

I am submitting the revised manuscript “Changing spatial patterns of stand-replacing fire in California conifer forests” to be considered for publication as an original research paper in *Forest Ecology and Management*.

We have fully addressed the helpful comments from two reviewers, including clarifying the relationship between weather and our other explanatory variables, clarifying that fuels were not directly assessed, adding a map figure and revising figures 2, 3 and 4 as requested by both reviewers. We believe the manuscript is much improved and appreciate the reviewers’ thoughtful feedback.

I apologize for the additional 1-week delay beyond the initial 1-week extension that was granted by the editor. Summer schedules were difficult to coordinate among co-authors with pre-existing vacations and fieldwork schedules.

I certify that the accompanying manuscript, and the data contained therein, has not been published and is not under consideration for publication with another journal. On behalf of my coauthors I have approved the current version this manuscript for publication with *Forest Ecology and Management*.

Sincerely,

A handwritten signature in black ink that reads "Jens T. Stevens".

Dr. Jens T. Stevens
Department of Environmental Science, Policy and Management
University of California Berkeley
Berkeley, CA 94720

-Reviewer 1

This paper uses a recently developed metric, called the 'stand-replacing decay coefficient' (SDC), to summarize high severity fire for each of over 450 fires in NW California over the 1984-2015 time period. The SDC provides more information compared to metrics such as 'high severity patch size' in that it considers the interior distance from areas that are burned with a lower severity; areas that burned with lower severity likely have retained live trees that can supply seeds to areas that experienced stand-replacing fire. The authors look for differences in SDC among different managing agencies, over time, between fire management strategies (suppression vs. managed/WFU fires), and over varying weather conditions. This is a well-written paper and provides a valuable scientific contribution.

We thank the reviewer for their positive feedback and for their useful suggestions below.

Below are some concerns and suggestions:

One of my more major concerns pertains the how weather was characterized. Using Tmax as an example, different biophysical settings inherently have different Tmax. Lower elevations will, on average, have higher Tmax than higher elevations. Since CDF-managed fires are usually at a lower elevation than other fires, it is only natural that Tmax will be higher for CDF fires. Could this influence your interpretations? Also, native Tmax units (degrees C) are difficult to properly interpret when study areas cover broad geographic extents. For example, the mean Tmax for CDF-managed fires is 32.7 degrees C. Is this warmer than normal (for the specific geographic location) or cooler than normal (for the specific geographic location)? This value of 32.7 degrees C is much higher than the USFS-managed WFU fires (24.9 degrees C), but because these fires occurred in different biophysical settings, it is impossible to ascertain whether these Tmax values are hotter/cooler than average. Are WFU fires burning under 'normal' conditions? Are CDF-managed fires burning under 'normal' conditions? This is important because the species composition of any given site are usually acclimated to the weather and climate conditions of the site, and therefore, the fire regimes and the SDC would be expected to differ among biophysical settings. Perhaps the 'counterintuitive result' reported on line 352 is because the Tmax units are not normalized to the average temperature of any given site. Simply put, I think what is more interesting is the deviation from average. Consequently, a potentially more informative approach in characterizing Tmax is to characterize in terms of percentile or z-score Tmax. All this said, calculating percentiles or z-scores is time consuming. If the authors choose not to follow my suggestion, I think this particular caveat should be mentioned in the Discussion. For more info on the percentile idea, I believe Dillon et al. (2011; *Ecosphere*) and Birch et al. (2015; *Ecosphere*) used weather percentile data.

These are good and important points. We carefully weighed whether to relativize the weather data, and decided against it for the following reason: We believe that

modeling SDC on absolute weather conditions indicates just how important fire weather is for influencing stand-replacement patterns, irrespective of biophysical settings. Fire behavior responds to absolute weather conditions, not relative conditions. To the extent that geographic differences in our different agency/class combinations are associated with differences in “normal” weather, we think it is important to highlight these differences as contributing ultimately to the size and configuration of stand-replacing fire effects. We have strived to be transparent about these geographic differences throughout the manuscript; that is one of the reasons why we included Table 2. For instance, the fact that the National Parks are generally located at higher elevations may explain the differences in TMax under suppression conditions (Table 2), but interestingly the average TMax under WFU conditions are almost identical between NPS and USFS, suggesting that each has opportunities to manage fire under less extreme conditions.

Regarding the acclimation of species composition to the regional climate and fire regime, while it is true that tree species in lower-elevation forests are generally more fire-resistant and might be expected to show less stand-replacement, these adaptations are largely overridden by changes in forest structure which, in concert with weather, are leading to increasingly large patches of stand-replacing fire, as our data show. It would be difficult to attribute regional differences in stand-replacing fire to deviations from normal climate as opposed to other land use changes that have rendered formerly heterogeneous, low-density stands more susceptible to stand-replacing fire. And regarding the “counterintuitive result”, we feel quite confident in the assertion that the fires that fall into this category are the result of the unique topography of the Klamath Mountains, particularly during the 1987 fire season, when inversions reduced fire activity despite high absolute temperatures, as previous work by Miller et al. (2012) has indicated.

We appreciate the reviewer’s larger point that the relationship between weather and our management variables is an important one, and we have made this connection more explicitly on **lines 338-348**.

I feel like some of the inferences regarding ‘management history’ and ‘fuels’ might be overstated. In my opinion, since you did not directly evaluate management history (e.g. last time thinned) or fuels, some of these inferences should be toned down. Also, because CDF-managed fires may be on either USFS or NPS land, ‘management history’ becomes more convoluted.

This is a good point, management agency is a coarse proxy for management history and does not represent fuels. We have revised the text and are now clearer about the limitations of this proxy, and have incorporated the reviewer’s specific comments on this topic below (e.g. **Lines 349-366**).

Unrelated to this paper, a potential avenue for future research may be to compare contemporary SDC values to historical SDC values to look for departures. One might expect that contemporary SDC values are smaller compared to some historic period.

Obviously, getting 'historic' SDC is not easy, but maybe a simulation model or using historical aerial photos could be of use.

This is a good idea and one we have been thinking about, particularly with respect to historical aerial photos. We are in initial discussions with some collaborators about attempting this. We note that the addition to this paper of a new website app (line 401), which allows users to upload shapefiles of their own stand-replacing patches of interest, should open the possibility of this type of application being more widely attempted going forward.

Here are some specific comments

1. Line 23: 'spatial scale' might be a little esoteric for an abstract. How about 'patch size' or something to that effect?

Done. Now L23-24

2. Line 30: 'past forest management'. This is a good example of overstating your inferences about fuels (second point above).

Agreed, as we describe below in response to the reviewer's comment #8, we now distinguish between management class (WFU vs suppression) and management agency, and collectively refer to them as "fire management". Without wanting to make this distinction in the abstract, we now simply refer to "fire management" here and are clear about management class, management agency, and the inferences that can be drawn from each variable, throughout the rest of the manuscript. Now L30

3. Line 53: is 'top-killed' the correct term? Why not simple killed.

Top-killed is generally used to describe a situation where the aboveground portion of the plant is killed, but resprouting may occur. In the mixed-conifer forests where we focus, this is generally not an issue as the dominant conifers do not re-sprout, but since the remote sensing techniques to assess burn severity (RdNBR) only measure aboveground "mortality" rather than permanent mortality, we believe this phrase is more technically accurate to the process at hand and wish to retain it. Now L54

4. Line 87: consider changing 'scale' to 'resolution'.

Done. Now L89

5. Line 110: consider adding ', and therefore type conversion,' (or something like that) between 'conifers' and 'compared'.

Good suggestion, done. Now L112.

6. Line 154: I believe this is the first mention that this study was conducted in NW California. It should be mentioned in the Abstract and Introduction. On a similar note, a study area figure would be nice.

We do introduce California as the general study area in the Abstract but we now identify the NW CA/Sierra Nevada focus in the introduction on **Line 135**. At the reviewer's suggestion we have included a study area figure as Figure 1.

7. Line 157: need a comma after 'for our analysis'.

Done. (now L161)

8. Line 196: Again, 'land management history' is inferred. Better labeling as 'managing agency' or something like that. 'Fire management' refers to suppression vs. WFU, right? If so, I recommend labeling as 'fire management' throughout and not as 'management' as to avoid confusion.

Good points, we have distinguished "fire management agency" from "fire management class" throughout, and we use "management" to refer to the two together. Now L205

9. Line 199: I'm only guessing you used GLMs here (due to the R package). I think you need to explain this much better.

10. Line 208: It is not clear why you used CART in addition to GLMs. Please clearly explain your rationale.

Re: comments 9 and 10. we used linear models (because the transformed data were normally distributed) to compare alternative models, and having selected the best model, we used CART to visualize the model and identify important thresholds in the predictor variables. We now clarify this in the paragraph on lines 205-225.

11. Line 215: Is it necessary to do the five year averages? I think the CIs in the figures provide a clear enough illustration. Plus, due to temporal autocorrelation (line 216), the R2 values for the five-year averages are bogus since each observation is not independent.

This is a fair point, we removed the five-year averages.

12. Line 221: I'd call it 'fire management class' to avoid ambiguity.

Done. Now L233

13. Line 237 (and elsewhere): perhaps back-transforming the values back to native SDC units is pertinent. SDC itself is hard enough to understand, but reporting the log-transformed units complicates even further.

Good point; we are already presenting both transformed and untransformed SDC values in the discussion, and now we do that here as well (Lines 255, 256). We choose to report both rather than only the untransformed values because both our GLM and CART analyses were done on the transformed data to meet assumptions of normality. Reviewer 2 also had this suggestion.

14. Line 250: 'the reduction' – should this actually be 'larger SDC values'?

Yes good catch; we have changed this and carefully checked the manuscript for similar mistakes (also changing "smaller" to "larger" on Line 372 and 406).

15. Line 271: 'averaged across all fires within a given year' – this appears to be the case for all plots. I recommend moving this up and perhaps including the figure legend.

Correct; we now specify that the SDC values in this section are averaged annual values, and that the weather parameters analyzed are average annual values of the maximum weather values during a particular burn window (lines 278-286), and we include this information in the Figure 3 caption.

16. Line 276: 'Consistent with previous ...' – this statement is Discussion material.

Good point, we now raise this discussion in the context of the uniqueness of the Klamath Mountains, lines 381-383.

17. Line 289: In addition to reporting the total area, what about the proportion of area burned managed by each agency? USFS has by far the most area of 'potential forest loss' but USFS presumably has the most area burned. Is USFS doing better/worse proportionally than CDF or NPS. Would be good to add to figure 4 as well.

We have added this statistic to the paragraph in question (now lines 296-297), and also to the caption for Figure 4.

18. Comma after 'previous work'.

Done (Assuming the reviewer was referring to the first paragraph of the discussion).

19. Line 314: Westerling is probably not the best cite here. They did not explicitly look at 'anticipated changes in climate and fire frequency'. Maybe something by Jeremy Littell or Sean Parks' in press article in Ecography.

Good suggestions, we added Jeremy's and Sean's papers to this statement. We also believe Westerling's paper is appropriate insofar as area burned is concerned, because the regional focus (climate projection models downscaled to California, and

chosen for their accuracy for that particular region) is actually the most appropriate to our study of the three papers, so we added area burned to the statement and retained the Westerling citation.

20. Line 317: 'our results corroborate this' – again, you did not explicitly evaluate fuels, so this is a bit overstated.

Fair point, we have toned down our language. Now L324.

21. Line 331: Did Abatzoglou and Williams even evaluate fuels? Similarly, I feel like most studies found a minimal to negligible influence of weather on fire severity. In my opinion, this is partially because it is terribly difficult to characterize weather.

Thanks, the reviewer is right that Abatzoglou and Williams looked at fuel moisture rather than fuel loads (which we implied). Based on this comment we decided to remove this sentence entirely. The point is not entirely pertinent to the results we present. Now ~L351.

22. Line 354: Do you mean 'larger' SDC values?

Yes, see above in response to reviewer's comment #14.

23. Line 380: 'desirable' is a subjective term.

Good point, we have clarified the specific patch size associated with the thresholds we identified rather than calling them "desirable".

24. I think a figure up front illustrating SDC would be useful since it is kind of difficult to understand. In theory, you could move figure 5 up.

The Collins et al. 2017 citation gives a detailed explanation of SDC and examples of how it is calculated; however we agree that more information in this paper would also be useful, so we have modified a figure from Collins et al. and included it in the Appendix as Figure A1.

25. Figure 2: I recommend making it more apparent in the legend that the x-axis in the left column is high severity fire and the right column is area burned. Took me longer than expected to figure it out.

We have added column headers to each side to further clarify the difference between them.

26. Figure 3: again, I'm not sure the five year mean column is necessary and I think the R² values are inflated.

Agree, we have removed them.

27. Figure 5: inclusion of the fire perimeters would be nice.

We now display the fire perimeters underneath the stand-replacing area in Figure 5.

28. I think that Meyer (2015; Journal of Forestry), Chambers et al. (2017; FEM), and Cansler and McKenzie (2014; Ecological Applications) are relevant studies that should be cited.

These are great recommendations – we are familiar with all of them and have incorporated them where relevant.

-Reviewer 2

The manuscript, "Changing spatial patterns of stand-replacing fire in California mixed-conifer forests" applies a novel fire severity method to describe changes in high severity fire patterns wildfires over time and across different public land ownerships within California, USA. This manuscript represents a very thoughtful applied contribution of the SDC metric to understanding landscape-level fire patterns across fire prone ecosystems and is a natural extension of the original Landscape Ecology article. I suggest this article should be accepted with minor revisions. My comments are made to help in readability and accessibility to those unfamiliar with the methods presented here.

Thank you for these positive comments; we appreciate the suggestions below.

Minor edits

Page 4-6 lines 80 – 116: These two paragraphs provide a lengthy defense that 1) high-severity classified RdNBR values are representative of stand-replacing fires, and 2) the SDC concentrates on high-severity patches given that regeneration failures are most likely to occur in these patches, and 3) mixed severity patches include fine-scaled variability in tree mortality, but the ecological implications of this variability are different given their closer proximity to a replenishing seed source. This section could be revised and shortened, in my opinion, given that previous articles (cited on line 93) have shown the RdNBR cutoffs developed for this region are reliable and representative of the mortality levels cited on line 89, and the previous SDC Landscape Ecology article makes the argument for the grain of the analysis. It seems the authors are trying to preemptively take a rock out of the road where none exists.

We agree with the reviewer's assessment of the intention of these two paragraphs,. We use the widely used terminology of low, moderate and high (or stand replacing) to describe fire severity at the level of the mapped pixel. We use the term "mixed-severity" to describe fires that contain stand-replacing (high severity) patches of

varying size and shape (lines 109-113). We appreciate the reviewer's suggestion to condense this material, and we acknowledge their point that some of these points are made in Collins et al. 2017. However we think that this detailed explanation of the importance of spatial scale in the definition of mixed-severity fires is critical to reiterate here, because this term is a "rock in the road" when it is used inappropriately: If most fires are mixed-severity fires based on the percentage thresholds, then "mixed-severity fire" becomes meaningless as a term to distinguish widely divergent post-fire environments that depend on stand-replacing patch sizes. Furthermore, we believe it is absolutely critical to remind readers that although basal area mortality greater than thresholds such as 70% or 90% may be used to classify RdNBR values into high severity classes, the vast majority of the area within these patches is true stand-replacing fire with 100% mortality, which the citations on Line 99 make clear. If the editor believes length of the manuscript is a concern, we would be willing to condense some of this material.

Page 8, line 164: It should be made clear 1) what RdNBR cutoff value was used to define high-severity, 2) that the ">90% basal area mortality" is estimated from the RdNBR itself, 3) that the polygons were essentially patches of high-severity within a fire that were delineated by aggregating adjacent pixels of like severity class in a GIS.

This is a helpful set of suggestions that we have implemented on lines 195-200.

Page 11, line 231, Management class isn't really a first-order control, it is the extinguishment of the flaming front that is the first-order control; management class should be referred to as A primary or THE primary predictor of SDC in your model.

Good point; the rpart analysis assigns the classification tree hierarchy based on importance values, so management class is statistically the most important predictor of SDC; we have made this change on line 280.

Page 11, line 237. The SDC scale itself is hard enough to decipher, and the $\ln(\text{SDC})$ is pretty esoteric. I suggest using the original scale (put \ln value in parentheses if it is required) and maybe it would be helpful to scale the scores that are being referenced to the min/max of all observed fires, to get a sense of where these scores lie in relation to the sample of fires assessed here. So, small and complex shaped patches could score near the lower quartile, while larger and more simple shaped patches could score in the upper quartile.

Good point; we are already presenting both transformed and untransformed SDC values in the discussion, and now we do that here as well (Lines 255, 259). We choose to report both rather than only the untransformed values because both our GLM and CART analyses were done on the transformed data to meet assumptions of normality. Reviewer 1 also had this suggestion. With respect to a quartile analysis, we believe that Figure A1, referenced here, along with the distribution of $\ln(\text{SDC})$ values present in Figure 2 collectively give the reader a good idea of the range of possible SDC values. We also believe that reporting the actual value rather than a

standardized version lets the user calculate the proportion of their stand-replacing area that is greater than a given distance from the patch edge using Eq. 1.

Page 11, line 231-246: this paragraph is fairly hard to follow. I would break it into comparisons between main effects. I.e., main differences between SDC among land ownerships, main influences of temperature, main influence of suppression, etc. After discussing the main effects, any nuisances can be discussed, but I would avoid merely running the readers down the tree.

Good point, we simplified our summary in this paragraph to focus on the main effects and trends (now lines 281-297).

Page 11. Did you consider putting wildfire size as a predictor in the CART model? If it were a main predictor then it may show different relationships further down the tree, and the cutoff value (s) in the tree may have important ecological or management implications.

Fire size is loosely correlated with SDC (Figure 2b, d), but we believe that many of the variables that we used in the CART model also predict fire size as well as SDC (as they relate to climate and fuels management), so fire size makes more sense as a response variable than a predictor variable. The fact that SDC is correlated with fire size is related to the fact that larger fires can have larger patches within them. A strength of SDC is that it is related to fire size but it more directly relates to the biological processes that drive the post-fire ecology.

Page 17, line 372. Not sure that low SDC is an indicator of mega-fire, but rather a consequence of mega-fires.

We agree that indicator might not be the best word; we have chosen to go with “characteristic of mega-fires”, as we think that checking the SDC may be a useful way to identify a “mega-fire”.

It was interesting that burning index was not a significant predictor of SDC given that it has been associated with high-severity fires in past studies (i.e., Lydersen et al. 2017 cited in the current document). This may be caused by 1) the methods used ascribe a single BI value across an entire fire area as was done here, or 2) there is a mismatch in scale from daily BI and the size of high-severity patches, or 3) the reliance on a remote measure of BI from a weather station not proximal to the high-severity patches themselves, or 4) a greater influence of fuels over fire weather. I suggest discussing the lack of an influence of BI on SDC in the discussion as it may prompt future work. For instance using SDC metrics for individual burn days using fire progression and severity maps (and potentially fuels or fuels surrogate maps) to help determine drivers of large-scale high severity fire patches.

Yes this is a good question, we now discuss this on lines 410-421.

Figure 1. The rpart figure is a bit tricky to read for those uninitiated in regression tree plots. For instance, it is not always intuitive to know which direction to walk down the tree given a continuous value at the break. 1) Please provide some instance in the caption, 2) it may be useful to mimic what the authors did for the first break (class = suppression) and have the labels on either side of the break. For instance, for max high temp, the label of the break could be Max high temp and to the left could be '> 24' and to the right '< 24'. For agency it could be label 'USFS', and to the left 'Yes', and to the right 'No', etc. Furthermore, the values of the ln(SDC) are hard to interpret in a stand-alone graph, particularly without any explanation in the caption. At the very least untransform the variable, but it may also be helpful to color the boxes based on the quantiles of the SDC values across fires to get a sense of how these values compare to the empirical distribution of the observed fires. Ie., is $\exp(-5.1)$ in the upper 90% of all fires? So, the coloring could go from blue to red with red indicating values in the upper quartile of observed fire values and blue the lower quartile. It would also be nice to know the sample size in each bin.

These are excellent points. We updated this figure to now make the breaks in the tree clearer, avoid the "Yes/No" confusion that the reviewer pointed out, and provided context for the ln(SDC) values by providing a histogram of all values for the 477 fires analyzed (New Figure 2). We adopt a color scheme along the lines of what the reviewer suggested. We chose not to untransform the variable because as we described earlier, the log transformation is necessary for the data to be normally distributed (as the histogram demonstrates), and all analyses were done on the log-transformed data. However we believe the new figure is much improved and we thank the reviewer for their comments.

Title

Changing spatial patterns of stand-replacing fire in California mixed-conifer forests

Highlights

- A novel metric for analyzing spatial pattern in stand-replacing fire is analyzed
- Stand-replacing patches have become larger and more regularly-shaped over time, particularly in the Sierra Nevada
- Wildland fire use and higher temperatures contribute to this change in spatial pattern
- Fine-grained spatial pattern of stand-replacing fire should be a management objective
- A web application is introduced to allow users and managers to calculate this metric for a fire of interest: stevensjt.shinyapps.io/sdc_app

1 **Running Head**

2 Spatial patterns of stand-replacing fire

3 **Title**

4 Changing spatial patterns of stand-replacing fire in California conifer forests

5 **Authors**

6 Jens T. Stevens ^{1*} Brandon M. Collins ² Jay D. Miller ³ Malcolm P. North ^{4,5} Scott L. Stephens ¹

7

8 **Author Affiliations and Addresses**

9 ¹Department of Environmental Science, Policy and Management, University of California,

10 Berkeley, CA, 94720

11 ²Center for Fire Research and Outreach, University of California, Berkeley, CA, 94720

12 ³USDA Forest Service, Pacific Southwest Region, Fire and Aviation Management, McClellan,

13 CA 95652

14 ⁴Department of Plant Sciences, University of California, Davis, CA 95616

15 ⁵USDA Forest Service, Pacific Southwest Research Station, Davis, CA 95618

16 *Corresponding Author. E-mail: stevensjt@berkeley.edu, Telephone: 781-630-3788.

17

18 Original Research Paper

19 **Abstract** [405 words]

20 Stand-replacing fire has profound ecological impacts in conifer forests, yet there is
21 continued uncertainty over how best to describe the scale of stand-replacing effects within
22 individual fires, and how these effects are changing over time. In forests where regeneration
23 following stand-replacing fire depends on seed dispersal from surviving trees, the size and shape
24 of stand-replacing patches are critical metrics that are difficult to describe and often overlooked.
25 We used a novel, recently-developed metric that describes the amount of stand-replacing area
26 within a given distance of a live-tree patch edge, in order to compare fires that may be otherwise
27 similar in fire size or the percentage of stand-replacing effects. Specifically, we analyzed 477
28 fires in California pine, fir, and mixed-conifer forests between 1984 and 2015 and asked whether
29 this metric, the stand-replacing decay coefficient (SDC), has changed over time, whether it is
30 affected by fire management, and how it responds to extreme weather conditions at the time of
31 the fire. Mean annual SDC became smaller over time (significantly so in the Sierra Nevada
32 region), indicating that stand-replacing patches became larger and more regularly shaped. The
33 decrease in SDC was particularly pronounced in the years since 2011. While SDC is correlated
34 with percent high-severity, it is able to distinguish fires of comparable percent high-severity but
35 different spatial pattern, with fires managed for suppression having smaller SDC than fires
36 managed for resource benefit. Similarly, fires managed by the US Forest Service had smaller
37 SDC than fires managed by the National Park Service. Fire weather also played an important role,
38 with higher maximum temperatures generally associated with smaller SDC values. SDC is useful
39 for comparing fires because it is associated with more conventional metrics such as percent high-
40 severity, but also incorporates a measure of regeneration potential – distance to surviving trees at
41 stand-replacement patch edges – which is a biological legacy that directly affects the resilience

42 of forests to increasingly frequent and severe fire disturbances. We estimate that from 1984-2015,
43 over 80,000 ha of forestland burned with stand-replacing effects greater than 120 m in from
44 patch edges, denoting areas vulnerable to extended conifer forest loss due to dispersal limitation.
45 Managing unplanned ignitions under less extreme weather conditions can achieve beneficial
46 “fine-grained” effects of stand-replacing fire where regeneration limitation is less of a concern.
47 Because SDC is a useful single metric to compare fires, we introduce a web application to
48 calculate SDC for any high-severity spatial layer that may be of interest.

49 **Keywords:** California; high-severity; mixed-conifer forests; patch dynamics; stand-replacing;
50 wildland fire

51 **Introduction**

52 In forests, overstory tree mortality from fire is an important ecological process that
53 catalyzes change in forest structure, fuel loads, vegetation diversity and wildlife habitat
54 suitability (Swanson *et al.*, 2011). Tree mortality from fire is a binary process (a tree is top-killed
55 or not), but it is spatially correlated: weather, fuel or topographic conditions that lead to the
56 mortality of one tree also increase the likelihood of mortality for neighboring trees (Collins *et al.*,
57 2007; Thompson and Spies, 2010). When a patch of adjacent trees are all top-killed by fire, this
58 is termed “stand-replacing fire”. This term is scale-independent – stand-replacing fire can refer to
59 sub-ha stands of ≤ 100 trees, or to many-ha stands of $> 10,000$ trees – but the implications of the
60 spatial scale of stand-replacing fire are profound.

61 Forest resilience, defined as long-term ecosystem persistence and capacity to recover
62 following perturbation (e.g. stand-replacing fire), depends on ecological memory in the form of
63 tree propagules (Holling, 1973; Johnstone *et al.*, 2016). In forests where the dominant tree
64 species have evolved to propagate after being top-killed by fire, (e.g. via basal re-sprouting in

65 oaks (*Quercus spp.*) or serotinous cones in Rocky Mountain lodgepole pine (*Pinus contorta var.*
66 *latifolia*)), resilience is maintained even in large stand-replacing patches. In forests where the
67 dominant tree species lack these adaptations (e.g. many western mixed-conifer forest types), tree
68 propagules generally must arrive via surviving trees on the edges of stand-replacing patches, and
69 the size and shape of these patches becomes critical. Forest resilience is reduced when
70 contiguous stand-replacing patches become larger because tree regeneration towards patch
71 interior is slowed by dispersal limitation, and the likelihood of future stand-replacing fire within
72 these patches increases (Stevens *et al.*, 2014; Chambers *et al.*, 2016; Coppoletta *et al.*, 2016;
73 Johnstone *et al.*, 2016; Welch *et al.*, 2016).

74 What drives much of the concern over stand-replacing fire in mixed-conifer forests is not
75 an intrinsically negative effect of stand-replacing fire, but the potential for large-scale tree
76 regeneration failure and persistent type-conversion (Millar and Stephenson, 2015). As such, there
77 have been numerous attempts to quantify trends in the extent of stand-replacing fire in
78 contemporary wildfires and infer how climate and forest management practices (e.g. historical
79 fire suppression and firefighting tactics) might influence these trends (Miller *et al.*, 2009b; Miller
80 and Safford, 2012; Miller *et al.*, 2012b; Cansler and McKenzie, 2014; Harvey *et al.*, 2016b;
81 Picotte *et al.*, 2016).

82 Most efforts to quantify trends in stand-replacing fire rely on interpretation of satellite-
83 based vegetation change indices, particularly the differenced Normalized Burn Ratio (dNBR)
84 (Key and Benson, 2006) and a version of that ratio relativized to pre-fire vegetation cover
85 (RdNBR) (Miller and Thode, 2007). Burn severity (the amount of dominant vegetation killed or
86 consumed by fire within a given area) can be estimated by calibrating this ratio to field-derived
87 data on canopy cover loss from fire, basal area loss from fire, or other composite field indices of

88 burn intensity (Miller *et al.*, 2009a). Modern burn severity classifications transform a continuous
89 variable (e.g. RdNBR) into a discrete variable, generally at a 30-m LANDSAT pixel resolution
90 (e.g. “low”, “moderate” or “high” severity), based on threshold values associated with particular
91 field conditions (e.g. $\leq 20\%$, 20-70%, or $> 70\%$ basal area mortality). Field validations of post-fire
92 conifer stands mapped as “high-severity”, whether using a 70% or a 90% basal area mortality
93 threshold, indicate these areas generally have $> 95\%$ basal area mortality, with 100% basal area
94 mortality being by far the most common condition greater than 30 m from the edge of a patch
95 mapped as “high-severity” (Miller and Quayle, 2015; Lydersen *et al.*, 2016). Thus, areas of
96 “high-severity fire” mapped in this way are reasonable approximations of “stand-replacing fire”.

97 More recently, the term “mixed-severity” has become popular to describe individual fires,
98 or characteristic effects of multiple fires (i.e. fire regimes), wherein some fraction of burned area
99 experiences stand-replacing effects delineated in distinct patches (Hessburg *et al.*, 2016). While
100 portions a fire’s area that are mapped as low or moderate severity still have some tree mortality,
101 individual “mixed-severity fires” are commonly described as those with 20-70% of the fire area
102 mapped as high-severity (Perry *et al.*, 2011). This approach relies upon the concept that patches
103 of stand-replacing fire of *ecologically meaningful size* are those mapped as “high-severity” at 30-
104 m resolution (Collins *et al.*, 2017). Mixed-severity fires are therefore comprised of discrete
105 patches of stand-replacing fire, eventually filled in by grass, shrubs, or tree regeneration,
106 surrounded by surviving forest that burned at low- to moderate-severity. While the “patchy”
107 nature of mixed-severity fires leads to a wide range of potential stand-replacing patch sizes and
108 shapes, the conventional definition of a mixed-severity fire says nothing about these attributes.
109 Percent high-severity is a useful way to measure fire effects and compare among multiple fires,
110 as it is easily derived and interpreted (Miller *et al.*, 2009b). However, fires where the stand-

111 replacing effects are concentrated in a few large patches are much more susceptible to dispersal
112 limitation of regenerating conifers, and therefore prolonged type conversion to non-forest
113 vegetation, compared to fires with a similar percent high severity but more smaller patches
114 (Crotteau *et al.*, 2013; Kemp *et al.*, 2016; Welch *et al.*, 2016). For instance, the 2013 Rim Fire in
115 California's Sierra Nevada had a relatively modest proportion of burned area mapped as high
116 severity (~35%) but contained some of the largest contiguous patches of stand-replacing fire
117 found anywhere in the modern record (Lydersen *et al.*, 2017). Thus, there is a need to update
118 previous research on trends in the modern burn severity record by accounting explicitly for the
119 size and shape of stand-replacing patches (Collins *et al.*, 2017).

120 Our objective was to document trends in stand-replacing patch configuration in
121 California's mixed-conifer forest ecoregion over the past 33 years, using a novel metric
122 developed to describe how much stand-replacing patch area remains with increasing distance
123 inward from patch edges (Collins *et al.*, 2017). The stand-replacing decay coefficient (SDC) is
124 related to fire size, high-severity area, and proportion high-severity, as well as conventional
125 landscape metrics such as patch edge:area ratio (Collins *et al.*, 2017). However, this metric is
126 more biologically relevant than traditional metrics because it explicitly accounts for distance to
127 seed source within stand-replacing patches, and as a single metric it distinguishes among fires
128 that may be similar in terms of fire size or proportion high-severity but differ strongly in
129 aggregate distance to seed source, without needing to specify a specific (and arbitrary) dispersal
130 limitation distance (Collins *et al.*, 2017). Thus SDC can more directly identify fires that are
131 vulnerable to long-term conifer forest loss and potential type-conversion.

132 In this paper, we present analyses that build on previous work investigating trends in burn
133 severity and differences among land management agencies in California (Miller and Safford,

134 2012; Miller *et al.*, 2012b). More specifically, we include all mapped forest fires >80 ha that
135 occurred in northwestern California and the Sierra Nevada from 1984 through 2015, which spans
136 two historic multi-year droughts (1987-1992, 2012-2016), to investigate 1) whether fires with
137 different managing agencies and management objectives differed in SDC independently of fire
138 size and proportion high-severity, 2) how average SDC for these fires changed over time, and 3)
139 the role of weather conditions in determining SDC. These results illustrate how a process-based
140 quantification of fire effects can be used to describe changing fire regimes, and this could assist
141 forest managers in developing desired conditions in western US forests that once burned with
142 frequent, low-moderate severity fire regimes.

143 **Methods**

144 Fire behavior and effects are influenced by a multitude of factors, including, but not
145 limited to, past forest management actions, topography, weather and climate. Fires within
146 California are managed primarily by three different agencies; the National Park Service (NPS),
147 US Forest Service (USFS) and the California Department of Forestry and Fire Protection (CAL
148 FIRE). These agencies support very different land management objectives and as such, have
149 different fire management directives. For example, Yosemite, and Sequoia and Kings Canyon
150 National Parks have allowed many lightning-ignited fires to burn under specified conditions to
151 meet resource-management objectives since the early 1970's (van Wagtendonk, 2007). Although
152 some National Forests allow some 'resource benefit' fires in more remote, higher-elevation areas,
153 most fires are still suppressed (Stephens and Ruth, 2005). Fires managed by CAL FIRE generally
154 occur at lower elevations in the wildland urban interface (WUI), and therefore are always
155 aggressively suppressed. Beyond potential differences in fire management approaches, the lands
156 these agencies manage have quite different forest management histories. The combined effect of

157 these differences would be expected to result in different fire patterns among these agencies.
158 Because the complex topography of northwestern California can lead to complex patterns of
159 stand-replacing fire (Miller *et al.*, 2012b; Estes *et al.*, 2017), we also considered effects of region
160 (see below).

161 For our analysis, we selected all wildfires in California that burned between 1984 and
162 2015 where the following criteria were met: 1) at least 80 ha in size; 2) predominantly (>50%) in
163 yellow pine (*Pinus ponderosa* or *P. Jeffreyi*), fir (*Abies concolor* or *A. magnifica*) or mixed-
164 conifer forest according to the CALVEG classification scheme (Keeler-Wolf, 2007); 3)
165 occurring in the regions of northwestern California, the southern Cascades, or the Sierra Nevada
166 (see below); 4) predominantly (>50%) on land managed by either the US Forest Service or the
167 US National Park Service; and 5) having a mapped burn-severity classification layer available.

168 These criteria led us to a sample size of 477 fires (Figure 1). For each fire we defined the
169 location of stand-replacing patches as adjacent pixels where the RdNBR exceeded the threshold
170 associated with 90% basal area mortality (652 for extended assessments and 746 for initial
171 assessments: Miller *et al.*, 2009a; Miller and Quayle, 2015). These patches were converted to
172 polygon shapefiles by Region 5 of the US Forest Service and made available
173 (<https://www.fs.usda.gov/detail/r5/landmanagement/gis/?cid=stelprd3804878>).

174 We calculated the stand-replacing decay coefficient (SDC) for each fire following the
175 methods of Collins *et al.* (2017). SDC is defined as:

$$176 \quad P = \frac{1}{10^{SDC * D}} \quad \text{Eq. 1}$$

177 where P is the proportion of the original stand-replacing area in the fire that exceeds a given
178 buffer distance inward from the patch edge (D), and SDC is a free parameter fit by nonlinear
179 least squares estimation that simultaneously describes the size and complexity of stand-replacing

area. Smaller SDC values represent larger and/or less complex patches (Figure A1; Collins *et al.* 2017). We reasoned that not all edges are biologically equivalent, as outer edges of stand-replacing patches would be more likely to contribute conifer seed into the patch than edges of very small internal “islands” of surviving trees within stand-replacing patches that were mapped as \leq 90% basal area mortality but most often were mapped as having $>$ 75% basal area mortality. Therefore we filled in any “islands” of 9 contiguous 30 m pixels (0.81 ha) or smaller, and considered these part of the stand-replacing patch when calculating SDC. The distribution of SDC for our 477 fires was left-skewed so we conducted a natural log (ln) transformation, which improved normality of the data (Collins *et al.*, 2017).

For each fire we approximated the weather at the time of the fire using the GridMet database (Abatzoglou, 2013). We identified the start and end dates for each of our 477 fires. In rare cases where the end date was not known (N=35), we set the end date to seven days after the start date. We excluded cases where the start date was not known (N=4). We then calculated the centroid latitude and longitude coordinate of the high-severity area within a given fire, and downloaded the daily weather estimates from GridMet for the grid cell (4 km) overlapping that centroid during the burn period. Daily estimates were obtained for daily high temperature, low temperature, high relative humidity, and burn index under the assumption that daily extremes are more likely to influence fire behavior than daily averages (Collins *et al.*, 2007). For each fire we then identified the most extreme fire weather conditions for these four variables during the burn period (maximum high temperature [TMX], maximum low temperature [TMN], minimum high relative humidity [RH], and maximum daily burn index [BI]), and incorporated these variables into our database of fires. Rather than using the lowest relative humidity, we’ve focused on the minimum high relative humidity in order to capture the recovery (or lack thereof) in relative

203 humidity for a given burn period. Little RH recovery has been associated with greater fire growth
204 potential, and by extension, larger patches of stand-replacing fire (Rothermel, 1991).

205 To evaluate the influence of fire management class, fire management agency (collectively
206 referred to as “management”), and fire weather on variation in $\ln(\text{SDC})$, we compared a set of
207 candidate models predicting SDC based on all possible combinations of seven variables, using
208 automated model selection implemented in the R package *gelmulti* (Calcagno and de Mazancourt,
209 2010). The candidate models were linear models conducted on the natural log of SDC – $\ln(\text{SDC})$
210 – which was normally distributed among all fires (Collins *et al.*, 2017). The variables examined
211 were: fire year (1984-2015), fire management class (“class”; fire managed for resource benefit,
212 e.g., wildland fire use [WFU], or suppression [SUP]), management agency (National Park
213 Service [NPS], US Forest Service [USFS], CAL FIRE [CDF]), region (northwestern CA [NW;
214 Shasta Trinity National Forest and all National Forests west from there] and the Southern
215 Cascades/Sierra Nevada [SCSN; all National Forests east of Shasta-Trinity and south to Sequoia
216 and Inyo National Forests]), and the four weather variables (TMX, TMN, RH, BI). We selected
217 the top 5 candidate models on the basis of AIC comparisons, and compared the parameter effect
218 sizes across these models. With parameter effects consistent across the top five candidate models
219 (Table 1), we selected a simple model (model #2) for visualization via regression tree analysis
220 using recursive partitioning, implemented in the *rpart* package in R (Therneau *et al.*, 2010).
221 While the linear model comparison approach allowed us to evaluate the important predictor
222 variables of $\ln(\text{SDC})$ and estimate their parameters, the regression tree analysis identified an
223 importance hierarchy of the explanatory variables and provided simple visualization of the model
224 structure while identifying important breakpoints within the predictor variables (Therneau *et al.*,
225 2010).

226 We also analyzed temporal trends in $\ln(\text{SDC})$ as well as the weather variables TMX and
227 BI using linear regression. There was high inter-annual variability in all of these variables, and a
228 Durbin-Watson test implemented in the R package *car* showed no temporal autocorrelation for
229 any of these variables. Finally, we calculated the increase over time in cumulative stand-
230 replacing area greater than a specific threshold distance (120 m; Collins *et al.*, 2017) from the
231 patch edge, for each managing agency.

232 **Results**

233 The best model to explain variation in SDC always included fire management class, fire
234 management agency, fire year, and maximum daily high temperature during the burn window,
235 while it never included the minimum daily high humidity (Table 1). Effects of these predictors
236 were consistent: SDC decreased (patches became larger and/or more regular) from NPS to USFS
237 to CDF-managed fires, decreased from WFU fires to SUP fires, decreased over time, and
238 decreased with increasing maximum high temperatures. Region, maximum low temperature, and
239 maximum burn index were marginal additional predictors in some models (Table 1). The
240 majority of the fires in our study were USFS fires that were actively suppressed; these fires were
241 generally larger and burned under hotter conditions compared to NPS-managed fires or WFU
242 fires (Table 2).

243 The regression tree analysis indicated that the fire management class was the most
244 important predictor of SDC values, with larger SDC values – associated with smaller and/or
245 more complex patches – for WFU fires (Figure 2). SUP fires generally had smaller SDC values
246 that are associated with larger and/or simpler patches. Fire weather and managing agency were
247 important among SUP fires, with fires burning under cooler temperatures and managed by the
248 National Park Service generally having larger SDC values, and fires burning under warmer

249 temperatures and managed by the US Forest Service generally having smaller SDC values
250 (Figure 2). One exception was a group of fires burning under hot ($>39^{\circ}$ C) conditions which had
251 larger $\ln(\text{SDC})$ values (see Discussion). Among SUP fires where the maximum high temperature
252 during the burn window exceeded 24° C, the year of the fire was important, with recent fires
253 occurring during or after 2011 having the smallest mean SDC values of any group of fires. The
254 range of mean $\ln(\text{SDC})$ values in the regression tree groups is approximately equivalent to 1 ha
255 circular patches of stand-replacing fire ($\ln[\text{SDC}] = -3.8$, $\text{SDC} = 0.022$) for WFU fires, up to 12
256 ha circular patches of stand-replacing fire ($\ln[\text{SDC}] = -5.1$, $\text{SDC} = 0.006$) for fires burning since
257 2011 (Figure A2; Collins *et al.*, 2017).

258 SDC is related to fire size and percent high-severity because larger fires with more area
259 burning at high-severity will inherently have more area located farther from high-severity patch
260 edges (Collins et al. 2017). However, SDC provides additional information to distinguish fires
261 from each other within a given range of fire size or percent severity. For instance, the larger SDC
262 values in fires managed by NPS or in fires managed as WFU fires are not just due to these fires
263 being smaller in size or having lower percent high-severity (although these effects do exist).
264 Rather, within a given fire size or percent high-severity range, agency and class still influence
265 SDC (Figure 2). In a model of SDC conditional on class (SUP vs WFU) and either percent high-
266 severity or fire size, class has a significant marginal effect on SDC after accounting for percent
267 severity ($t = 5.35$, $P < 0.001$; Figure 3a) and size ($t = 7.92$, $P < 0.001$; Figure 3b). In a model of
268 SDC conditional on agency and either percent high-severity or fire size, agency also has a
269 significant effect on SDC after accounting for these variables (Figure 3c,d), with NPS
270 distinguishable from both USFS ($t = 5.54$, $P < 0.001$ after accounting for percent high-severity; t

271 = 7.07, P < 0.001 after accounting for fire size) and CDF ($t = 3.03$, P = 0.003 after accounting for
272 percent high-severity; $t = 5.78$, P < 0.001 after accounting for fire size), while the latter two are
273 indistinguishable from each other ($t = 0.16$, P = 0.877) after accounting for percent high-severity,
274 and marginally significantly different from each other ($t = 1.925$, P = 0.055) after accounting for
275 fire size.

276 Although fire management class and agency are clearly related to SDC values, the
277 relationship between fire year, weather during the fire, and SDC is more complex. Average
278 annual SDC decreased over time (Figure 4a), at a rate that was marginally significant ($R^2 = 0.11$,
279 $t = 1.97$, P = 0.058). The maximum average daily burn index during the time of a fire increased
280 significantly over time (Figure 4b; $R^2 = 0.32$, $t = 3.80$, P = 0.001). Similarly, the average annual
281 maximum high temperature during the time of a fire increased over time from 1984-2015 (Figure
282 4c), a trend that was marginally significant for individual year averages ($R^2 = 0.010$, $t = 1.83$, P =
283 0.077). However, while four of the six lowest average SDC values in the 31-year time period
284 occurred between 2011 and 2015, only one of the six highest average burn index years and two
285 of the six highest average temperature years occurred in this same period (Figure 4a). We also
286 found a significant decrease in annual average SDC over time in the Southern Cascades/Sierra
287 Nevada ($R^2 = 0.12$, $t = 2.05$, P = .049) but not in northwestern California ($R^2 = 0.004$, $t = 0.32$, P
288 = .750) (Figure A3).

289 SDC can be used to calculate the proportion of stand-replacing effects in a given fire
290 greater than a critical dispersal distance threshold in from the patch edge. This proportion can
291 thus be used to calculate the area in a given fire that will likely be void of substantive natural
292 conifer regeneration. When we calculated this area of potential “forest loss” for all fires in our
293 study using a common dispersal distance threshold of 120 m (Collins *et al.*, 2017), we found that

294 over 80,000 ha of stand-replacing fire in the study area since 1984 occurred more than 120 m
295 from a patch edge, with most of that area concentrated in fires managed by USFS (Figure 5).
296 This area represents 12.6% of total area burned for CDF fires, 7.8% of total area burned for
297 USFS fires and 3.0% of total area burned for NPS fires (Figure 5).

298 **Discussion**

299 The SDC tended towards smaller values (e.g. larger and less complex high-severity
300 patches) over time in fires managed for suppression, and on landscapes with a longer history of
301 suppressing almost all fires (e.g. USFS) (Stephens and Ruth, 2005; van Wagtendonk, 2007;
302 Meyer, 2015). These broad trends are generally consistent with previous work documenting
303 increases in the percentage of stand-replacing effects within a fire over time, and on USFS land
304 rather than NPS land in the Sierra Nevada (Miller *et al.*, 2009b; Miller *et al.*, 2012a; Miller and
305 Safford, 2012). However, in corroborating this previous work, our results provide important
306 additional information, because we quantify changes in the spatial patterns of stand-replacing
307 fire that directly reflect changes in post-fire regeneration potential (e.g. distance to seed source)
308 and potential loss of conifer forest, at least in the near term.

309 The advantage of SDC over metrics such as percent high-severity is that fires with similar
310 percentages can have dramatically different patch sizes that affect ecosystem recovery (Figure 3).
311 This can be visualized in Figure 6, which illustrates a set of comparison fires with similar percent
312 high-severity and similar fire area, but different spatial patterns and SDC values. SDC is a useful
313 addition to this existing set of metrics because it is a single metric, comparable across a large
314 number of fires, that simultaneously accounts for covariation in percent high-severity, area
315 burned at high-severity, edge:area ratio of high-severity patches, and other metrics that are
316 correlated with, but do not directly measure, the potential for dispersal limitation (Collins *et al.*,

317 2017). It is this dispersal limitation and resultant lags in forest regeneration, rather than
318 percentages of an area burning at high-severity *per se*, that may contribute to potential forest loss
319 and establishment of alternative stable states. (Millar and Stephenson, 2015; Coppoletta *et al.*,
320 2016; Harvey *et al.*, 2016a; Johnstone *et al.*, 2016). This potential is only exacerbated by
321 anticipated changes in regional climate, fire frequency and area burned (Littell *et al.*, 2009;
322 Westerling *et al.*, 2011; Parks *et al.*, 2017), which further increases the likelihood of high-
323 severity fires re-burning in short succession.

324 Weather and fuels can strongly influence fire severity and area burned (Safford *et al.*,
325 2012; Collins, 2014; Lydersen *et al.*, 2014; Parks *et al.*, 2015), and our results suggest that this is
326 the case for spatial patterns of stand-replacing fire as well (e.g., Cansler and McKenzie, 2014).
327 Under more moderate weather conditions, fire effects tended to be within the range of historical
328 variability for California conifer forests – smaller, more irregular patches of stand-replacing fire
329 generally < 2ha (Safford and Stevens, 2017). Maximum daily high temperature during the burn
330 period was an important factor and fires burning under cooler conditions generally had SDC
331 values around 4.1, associated with an average patch size of around 2 ha (Figure 2, Figure A1).
332 We were surprised that burn index was not identified as an important predictor of SDC. This
333 could be due to inaccuracies related to downscaling burn index in the climate data, or because
334 the maximum burn index during a burn window may be less relevant to stand-replacing fire than
335 the duration of periods with high burn index. Further work is needed that could examine more
336 sophisticated representations of weather tied specifically to the period and location of stand-
337 replacing patches with small SDC values.

338 Although management class emerged as the most important control over SDC (Figure 2),
339 this also reflects the influence of weather to some degree because decisions on whether to

340 manage fires are based partly on weather conditions (North *et al.*, 2012; Meyer, 2015). Our
341 dataset supports this, as “wildland fire use” fires tended to burn under cooler maximum high
342 temperatures than fires managed for suppression, regardless of agency (Table 2). Fires managed
343 for suppression in the NPS tend to have cooler maximum high temperatures than fires on USFS
344 land (Table 2), which might reflect the higher elevation of the three National Parks in the Sierra
345 Nevada relative to the majority of National Forest land (Figure 1). These results suggest there
346 may be opportunities for increased fire use on Forest Service land during the spring and fall,
347 when temperatures are lower, that would more closely mimic the fine-grained stand-replacement
348 patterns evident on National Parks land (Figure 1).

349 Although the influence of “fuels” on SDC is indirectly represented by our management
350 class variable and its connection with forest management history, relevant fuel characterizations
351 are largely lacking the spatial and temporal resolution that are available for weather variables.
352 Despite this limitation, several lines of evidence suggest that increased fuel loads are associated
353 with smaller SDC values. The trend towards smaller SDC values over time may reflect the effect
354 of fire suppression and associated fuel accumulation. However, California also experienced a
355 severe four-year drought from the winter 2011-2012 through the winter 2014-2015 (Young *et al.*,
356 2017), which likely had an effect on this trend. The years from 2011-2015 had four of the six
357 lowest mean SDC values of any year since 1984, and while maximum temperature and burn
358 index increased over this time period, only two of those years (2012 and 2015) were among the
359 six highest maximum temperature years based on burn-period temperatures, and only one (2012)
360 was among the six highest burn index years (Figure 4). Our regression tree analysis identifies
361 2011 as a threshold year, with fires occurring on or after that year having the smallest mean SDC
362 value of any cluster in the tree, after controlling for the effect of temperature (Figure 3). Smaller

363 SDC values for fires managed by the USFS compared to the NPS after controlling for weather
364 (Table 1), may indicate a longer history of fire suppression on USFS lands (Miller *et al.*, 2012a),
365 which have a broader array of constraints when considering how to manage ignitions (van
366 Wagtendonk, 2007).

367 Topography is also an important control over fire effects (Taylor and Skinner, 2003;
368 Lydersen *et al.*, 2014; Harris and Taylor, 2015; Estes *et al.*, 2017). In areas with high
369 topographic complexity, patterns of stand-replacing fire may be less responsive to variation in
370 fuels or weather (Miller *et al.*, 2012b). We found a seemingly counterintuitive result in our
371 regression tree analysis where fires with a maximum high temperature greater than or equal to
372 39°C had larger SDC values (N=18, Figure 2). Every one of these fires, however, occurred in the
373 northwestern part of California centered around the Klamath Mountains, with a majority (N=10)
374 occurring in 1987, a particularly warm year (Figure 4) with widespread lightning fire activity in
375 this region. Temperature inversions within the topographically complex Klamath region are
376 common when summer high-pressure systems setup over the region. The inversions have been
377 documented to trap smoke from wildland fire in valleys for weeks, reducing solar insolation and
378 daytime maximum temperatures in valleys relative to nearby ridgetops (Robock, 1988). As a
379 result daytime fire activity is suppressed in some areas, even in particularly warm years like 1987,
380 which can moderate fire behavior and reduce stand-replacing effects (Robock, 1988; Estes *et al.*,
381 2017). The topographic complexity of the Klamath Mountains may also explain why we did not
382 see a significant decrease in SDC over time in that region, but we did see a significant decrease
383 in the Sierra Nevada (Miller and Safford, 2012; Miller *et al.*, 2012b).

384 While it is difficult to ascribe strict causality to the observed trends in SDC, multiple
385 lines of evidence suggest that primary drivers are changes in weather and fuels. The ongoing

386 increase in both extreme weather frequency and fuel accumulation across many forested
387 landscapes (Collins, 2014; Millar and Stephenson, 2015; Safford and Stevens, 2017) are likely
388 contributing to larger and more regular stand-replacing patches. As such, the occurrence of so-
389 called “mega-fires”, where fire behavior and effects exceed the range of variability previously
390 observed, is expected to continue to increase over time unless substantive fuel reduction and
391 forest restoration efforts are implemented in the appropriate forest types (Stephens *et al.*, 2014b).

392 Low SDC values are characteristic of “mega-fires”, and their incidence appears to be on
393 the rise. These fires contribute disproportionately to the cumulative area of forest loss where a
394 dispersal distance threshold of 120 m is exceeded (Figure 5). For example, over the 32 years
395 from 1984-2015, 20 fires have had an SDC smaller than 0.0026. Of these 20 fires, half (10) have
396 occurred in the 9 years since 2007, including some well-known recent fires widely considered to
397 be “mega-fires”, including the 2007 Moonlight Fire (Stephens *et al.*, 2014a), the 2013 Rim Fire
398 (Lydersen *et al.*, 2014), and the 2014 King Fire (Jones *et al.*, 2016), which has the smallest SDC
399 of any of the 477 fires studied ($SDC = 0.0013$; $\ln(SDC) = -6.64$). Because SDC is a useful single
400 metric to compare fires, we have created a web application to calculate SDC for any high-
401 severity spatial layer (stevensjt.shinyapps.io/sdc_app). This ‘app’ allows a user to upload a
402 shapefile of stand-replacing patches in a metric coordinate system and compare a particular fire
403 against the SDC values of all 477 fires analyzed in this paper. This tool also allows for a
404 statistical comparison of fires from other regions outside of California that are thought to be at
405 risk for regeneration failure within stand-replacing patches (e.g., Chambers *et al.*, 2016)

406 Fires with larger SDC values indicative of smaller circular patches of 10 ha or less (e.g.
407 $SDC > 0.0067$; $\ln(SDC) > -5$; Figure A2) suggest a way forward for fire management that
408 incorporates some of the benefits of stand-replacing fire while not compromising long-term

409 forest resilience (Meyer, 2015). Wildfires that burn under moderate fire weather conditions or
410 are managed by agencies with a longer history of fire use are much more likely to have larger
411 SDC values, even if their percentage of high-severity effects are in the 20-40% range (Figure 3).
412 This is consistent with a large and developing body of literature suggesting that there are
413 opportunities for increased use of fire, in concert with mechanical fuels reduction in some
414 instances, during periods of time where rapid fire spread is not likely (Stephens *et al.*, 2013;
415 Millar and Stephenson, 2015; North *et al.*, 2015; Stephens *et al.*, 2016). There are many barriers
416 to the increased use of fire, but current trends in stand replacement spatial patterns mean that the
417 alternative could be increasingly large dead tree patches where forest regeneration is delayed for
418 extended periods of time.

419 **Acknowledgments**

420 This work was also supported by a research partnership between the US Forest Service
421 Pacific Southwest Research Station and UC Berkeley College of Natural Resources (project no.
422 16-JV-11272167-063). Zack Steel, Sean Parks, and two anonymous reviewers provided helpful
423 comments on earlier versions of this manuscript.

424 **Literature Cited**

- 425
- 426 Abatzoglou, J.T., 2013. Development of gridded surface meteorological data for ecological
427 applications and modelling. International Journal of Climatology 33, 121-131.
- 428 Calcagno, V., de Mazancourt, C., 2010. glmulti: an R package for easy automated model
429 selection with (generalized) linear models. Journal of Statistical Software 34, 1-29.
- 430 Cansler, C.A., McKenzie, D., 2014. Climate, fire size, and biophysical setting control fire
431 severity and spatial pattern in the northern Cascade Range, USA. Ecol. Appl. 24, 1037-1056.

- 432 Chambers, M.E., Fornwalt, P.J., Malone, S.L., Battaglia, M.A., 2016. Patterns of conifer
433 regeneration following high severity wildfire in ponderosa pine – dominated forests of the
434 Colorado Front Range. *For. Ecol. Manag.* 378, 57-67.
- 435 Collins, B.M., 2014. Fire weather and large fire potential in the northern Sierra Nevada. *Agric.*
436 *For. Meteorol.* 189–190, 30-35.
- 437 Collins, B.M., Kelly, M., van Wagtendonk, J.W., Stephens, S.L., 2007. Spatial patterns of large
438 natural fires in Sierra Nevada wilderness areas. *Landsc. Ecol.* 22, 545-557.
- 439 Collins, B.M., Stevens, J.T., Miller, J.D., Stephens, S.L., Brown, P.M., North, M.P., 2017.
440 Alternative characterization of forest fire regimes: incorporating spatial patterns. *Landsc. Ecol.*
441 32, 1543-1552.
- 442 Coppoletta, M., Merriam, K.E., Collins, B.M., 2016. Post-fire vegetation and fuel development
443 influences fire severity patterns in reburns. *Ecol. Appl.* 26, 686-699.
- 444 Crotteau, J.S., Morgan Varner Iii, J., Ritchie, M.W., 2013. Post-fire regeneration across a fire
445 severity gradient in the southern Cascades. *For. Ecol. Manag.* 287, 103-112.
- 446 Estes, B.L., Knapp, E.E., Skinner, C.N., Miller, J.D., Preisler, H.K., 2017. Factors influencing
447 fire severity under moderate burning conditions in the Klamath Mountains, northern California,
448 USA. *Ecosphere* 8, e01794-n/a.
- 449 Harris, L., Taylor, A.H., 2015. Topography, fuels and fire exclusion drive fire severity of the
450 Rim Fire in an old-growth mixed- conifer forest, Yosemite National Park, USA. *Ecosystems* 18,
451 1192-1208.
- 452 Harvey, B.J., Donato, D.C., Turner, M.G., 2016a. Burn me twice, shame on who? Interactions
453 between successive forest fires across a temperate mountain region. *Ecology* 97, 2272-2282.

- 454 Harvey, B.J., Donato, D.C., Turner, M.G., 2016b. Drivers and trends in landscape patterns of
455 stand-replacing fire in forests of the US Northern Rocky Mountains (1984–2010). *Landsc. Ecol.*
456 31, 2367-2383.
- 457 Hessburg, P.F., Spies, T.A., Perry, D.A., Skinner, C.N., Taylor, A.H., Brown, P.M., Stephens,
458 S.L., Larson, A.J., Churchill, D.J., Povak, N.A., Singleton, P.H., McComb, B., Zielinski, W.J.,
459 Collins, B.M., Salter, R.B., Keane, J.J., Franklin, J.F., Riegel, G., 2016. Tamm Review:
460 Management of mixed-severity fire regime forests in Oregon, Washington, and Northern
461 California. *For. Ecol. Manag.* 366, 221-250.
- 462 Holling, C.S., 1973. Resilience and stability of ecological systems. *Annu. Rev. Ecol. Syst.* 4, 1-
463 23.
- 464 Johnstone, J.F., Allen, C.D., Franklin, J.F., Frelich, L.E., Harvey, B.J., Higuera, P.E., Mack,
465 M.C., Meentemeyer, R.K., Metz, M.R., Perry, G.L.W., Schoennagel, T., Turner, M.G., 2016.
466 Changing disturbance regimes, ecological memory, and forest resilience. *Frontiers in Ecology*
467 and the Environment
- 468 14, 369-378.
- 469 Jones, G.M., Gutiérrez, R.J., Tempel, D.J., Whitmore, S.A., Berigan, W.J., Peery, M.Z., 2016.
470 Megafires: an emerging threat to old-forest species. *Frontiers in Ecology and the Environment* 14,
471 300-306.
- 472 Keeler-Wolf, T., 2007. The history of vegetation classification and mapping in California. In:
473 Barbour, M.G., Keeler-Wolf, T., Schoenherr, A.A. (Eds.), *Terrestrial vegetation of California*.
474 University of California Press, Berkeley, CA, pp. 1-42.
- 475 Kemp, K.B., Higuera, P.E., Morgan, P., 2016. Fire legacies impact conifer regeneration across
environmental gradients in the U.S. northern Rockies. *Landsc. Ecol.* 31, 619-636.

- 476 Key, C.H., Benson, N.C., 2006. Landscape assessment: remote sensing of severity, the
477 Normalized Burn Ratio. In: Lutes, D.C. (Ed.), FIREMON: Fire effects monitoring and inventory
478 system Ogden, Utah: USDA Forest Service, Rocky Mountain Res. Station, Fort Collins,
479 Colorado, USA, pp. LA25 - LA41.
- 480 Littell, J.S., McKenzie, D., Peterson, D.L., Westerling, A.L., 2009. Climate and wildfire area
481 burned in western U.S. ecoprovinces, 1916–2003. *Ecol. Appl.* 19, 1003-1021.
- 482 Lydersen, J.M., Collins, B.M., Brooks, M.L., Matchett, J.R., Shive, K.L., Povak, N.A., Smith,
483 D.F., 2017. Evidence of fuels management and fire weather influencing fire severity in an
484 extreme fire event. *Ecol. Appl.* *in press*.
- 485 Lydersen, J.M., Collins, B.M., Miller, J.D., Fry, D.L., Stephens, S.L., 2016. Relating fire-caused
486 change in forest structure to remotely sensed estimates of fire severity. *Fire Ecology* 12, 99-116.
- 487 Lydersen, J.M., North, M.P., Collins, B.M., 2014. Severity of an uncharacteristically large
488 wildfire, the Rim Fire, in forests with relatively restored frequent fire regimes. *For. Ecol. Manag.*
489 328, 326-334.
- 490 Meyer, M.D., 2015. Forest Fire Severity Patterns of Resource Objective Wildfires in the
491 Southern Sierra Nevada. *Journal of Forestry* 113, 49-56.
- 492 Millar, C.I., Stephenson, N.L., 2015. Temperate forest health in an era of emerging
493 megadisturbance. *Science* 349, 823-826.
- 494 Miller, J.D., Collins, B.M., Lutz, J.A., Stephens, S.L., van Wagendonk, J.W., Yasuda, D.A.,
495 2012a. Differences in wildfires among ecoregions and land management agencies in the Sierra
496 Nevada region, California, USA. *Ecosphere* 3, art80.
- 497 Miller, J.D., Knapp, E.E., Key, C.H., Skinner, C.N., Isbell, C.J., Creasy, R.M., Sherlock, J.W.,
498 2009a. Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to

- 499 three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA.
- 500 Remote Sens. Environ. 113, 645-656.
- 501 Miller, J.D., Quayle, B., 2015. Calibration and validation of immediate post-fire satellite derived
- 502 data to three severity metrics. Fire Ecology 11, 12-30.
- 503 Miller, J.D., Safford, H., 2012. Trends in wildfire severity 1984-2010 in the Sierra Nevada,
- 504 Modoc Plateau and southern Cascades, California, USA. Fire Ecology 8, 41-57.
- 505 Miller, J.D., Safford, H.D., Crimmins, M., Thode, A.E., 2009b. Quantitative evidence for
- 506 increasing forest fire severity in the Sierra Nevada and southern Cascade Mountains, California
- 507 and Nevada, USA. Ecosystems 12, 16-32.
- 508 Miller, J.D., Skinner, C.N., Safford, H.D., Knapp, E.E., Ramirez, C.M., 2012b. Trends and
- 509 causes of severity, size, and number of fires in northwestern California, USA. Ecol. Appl. 22,
- 510 184-203.
- 511 Miller, J.D., Thode, A.E., 2007. Quantifying burn severity in a heterogeneous landscape with a
- 512 relative version of the delta Normalized Burn Ratio (dNBR). Remote Sens. Environ. 109, 66-80.
- 513 North, M., Collins, B.M., Stephens, S., 2012. Using fire to increase the scale, benefits, and future
- 514 maintenance of fuels treatments. Journal of Forestry 110, 392-401.
- 515 North, M.P., Stephens, S.L., Collins, B.M., Agee, J.K., Aplet, G., Franklin, J.F., Fulé, P.Z., 2015.
- 516 Reform forest fire management. Science 349, 1280-1281.
- 517 Parks, S.A., Holsinger, L.M., Miller, C., Nelson, C.R., 2015. Wildland fire as a self-regulating
- 518 mechanism: the role of previous burns and weather in limiting fire progression. Ecol. Appl. 25,
- 519 1478-1492.
- 520 Parks, S.A., Holsinger, L.M., Miller, C., Parisien, M.-A., 2017. Analog-based fire regime and
- 521 vegetation shifts in mountainous regions of the western US. Ecography In Press.

- 522 Perry, D.A., Hessburg, P.F., Skinner, C.N., Spies, T.A., Stephens, S.L., Taylor, A.H., Franklin,
523 J.F., McComb, B., Riegel, G., 2011. The ecology of mixed severity fire regimes in Washington,
524 Oregon, and northern California. *For. Ecol. Manag.* 262, 703-717.
- 525 Picotte, J.J., Peterson, B., Meier, G., Howard, S.M., 2016. 1984–2010 trends in fire burn severity
526 and area for the conterminous US. *Int. J. Wildland Fire* 25, 413-420.
- 527 Robock, A., 1988. Enhancement of Surface Cooling Due to Forest Fire Smoke. *Science* 242,
528 911-913.
- 529 Rothermel, R.C., 1991. Predicting behavior and size of crown fires in the Northern Rocky
530 Mountains. In, USDA Forest Service, Intermountain Research Station.
- 531 Safford, H.D., Stevens, J.T., 2017. Natural Range of Variation (NRV) for yellow pine and mixed
532 conifer forests in the Sierra Nevada, southern Cascades, and Modoc and Inyo National Forests,
533 California, USA. In. USDA Forest Service, Pacific Southwest Research Station. General
534 Technical Report PSW-GTR-256, Albany, CA.
- 535 Safford, H.D., Stevens, J.T., Merriam, K., Meyer, M.D., Latimer, A.M., 2012. Fuel treatment
536 effectiveness in California yellow pine and mixed conifer forests. *For. Ecol. Manag.* 274, 17-28.
- 537 Stephens, S.L., Agee, J.K., Fulé, P.Z., North, M.P., Romme, W.H., Swetnam, T.W., Turner,
538 M.G., 2013. Managing forests and fire in changing climates. *Science* 342, 41-42.
- 539 Stephens, S.L., Bigelow, S.W., Burnett, R.D., Collins, B.M., Gallagher, C.V., Keane, J., Kelt,
540 D.A., North, M.P., Roberts, L.J., Stine, P.A., Van Vuren, D.H., 2014a. California spotted owl,
541 songbird, and small mammal responses to landscape fuel treatments. *Bioscience*.
- 542 Stephens, S.L., Burrows, N., Buyantuyev, A., Gray, R.W., Keane, R.E., Kubian, R., Liu, S.,
543 Seijo, F., Shu, L., Tolhurst, K.G., van Wagtendonk, J.W., 2014b. Temperate and boreal forest

- 544 mega-fires: characteristics and challenges. *Frontiers in Ecology and the Environment* 12, 115-
545 122.
- 546 Stephens, S.L., Collins, B.M., Biber, E., Fulé, P.Z., 2016. U.S. federal fire and forest policy:
547 emphasizing resilience in dry forests. *Ecosphere* 7, e01584-n/a.
- 548 Stephens, S.L., Ruth, L.W., 2005. Federal forest-fire policy in the United States. *Ecol. Appl.* 15,
549 532-542.
- 550 Stevens, J.T., Safford, H.D., Latimer, A.M., 2014. Wildfire-contingent effects of fuel treatments
551 can promote ecological resilience in seasonally dry conifer forests. *Can. J. For. Res.* 44, 843-854.
- 552 Swanson, M.E., Franklin, J.F., Beschta, R.L., Crisafulli, C.M., DellaSala, D.A., Hutto, R.L.,
553 Lindenmayer, D.B., Swanson, F.J., 2011. The forgotten stage of forest succession: early-
554 successional ecosystems on forest sites. *Frontiers in Ecology and the Environment* 9, 117-125.
- 555 Taylor, A.H., Skinner, C.N., 2003. Spatial patterns and controls on historical fire regimes and
556 forest structure in the Klamath Mountains. *Ecol. Appl.* 13, 704-719.
- 557 Therneau, T.M., Atkinson, B., Ripley, B., 2010. rpart: Recursive partitioning. R package version
558 3, 1-46.
- 559 Thompson, J., Spies, T., 2010. Factors associated with crown damage following recurring
560 mixed-severity wildfires and post-fire management in southwestern Oregon. *Landsc. Ecol.* 25,
561 775-789.
- 562 van Wagtendonk, J.W., 2007. The history and evolution of wildland fire use. *Fire Ecology* 3, 3-
563 17.
- 564 Welch, K.R., Safford, H.D., Young, T.P., 2016. Predicting conifer establishment post wildfire in
565 mixed conifer forests of the North American Mediterranean-climate zone. *Ecosphere* 7, e01609-
566 n/a.

- 567 Westerling, A.L., Bryant, B.P., Preisler, H.K., Holmes, T.P., Hidalgo, H.G., Das, T., Shrestha,
568 S.R., 2011. Climate change and growth scenarios for California wildfire. *Clim. Change* 109,
569 S445-S463.
- 570 Young, D.J.N., Stevens, J.T., Earles, J.M., Moore, J., Ellis, A., Jirka, A.L., Latimer, A.M., 2017.
571 Long-term climate and competition explain forest mortality patterns under extreme drought. *Ecol.*
572 *Lett.* 20, 78-86.
- 573
- 574

575 **Table 1:** Five best candidate models (model #1-5) of SDC, based on AIC comparison.
 576 Coefficients are relative to a model where: agency = CDF (CAL FIRE), class = SUP
 577 (suppression), and region = SCSN (Southern Cascades/Sierra Nevada), USFS = US Forest
 578 Service, NPS = US National Park Service, WFU = Wildland Fire Use, max_tmmx = maximum
 579 daily high temperature during burn window, max_tmmn = maximum daily low temperature
 580 during burn window, NW = northwestern region of California, max_bi = maximum daily burn
 581 index during burn window, and min_rmax = minimum daily high humidity during burn window.

Model AIC /coefficients	Model #				
	1	2	3	4	5
AIC	901.721	902.151	902.154	902.724	902.818
(Intercept)	7.136	5.557	7.66	5.423	5.972
agencyNPS	0.478	0.506	0.475	0.472	0.504
agencyUSFS	0.196	0.214	0.174	0.189	0.194
classWFU	0.377	0.379	0.381	0.401	0.381
fire_year	-0.006	-0.005	-0.006	-0.005	-0.005
max_tmmx	-0.024	-0.012	-0.028	-0.023	-0.015
max_tmmn	0.019		0.019	0.019	
regionNW			0.09		0.083
max_bi				-0.002	
min_rmax					

582

583

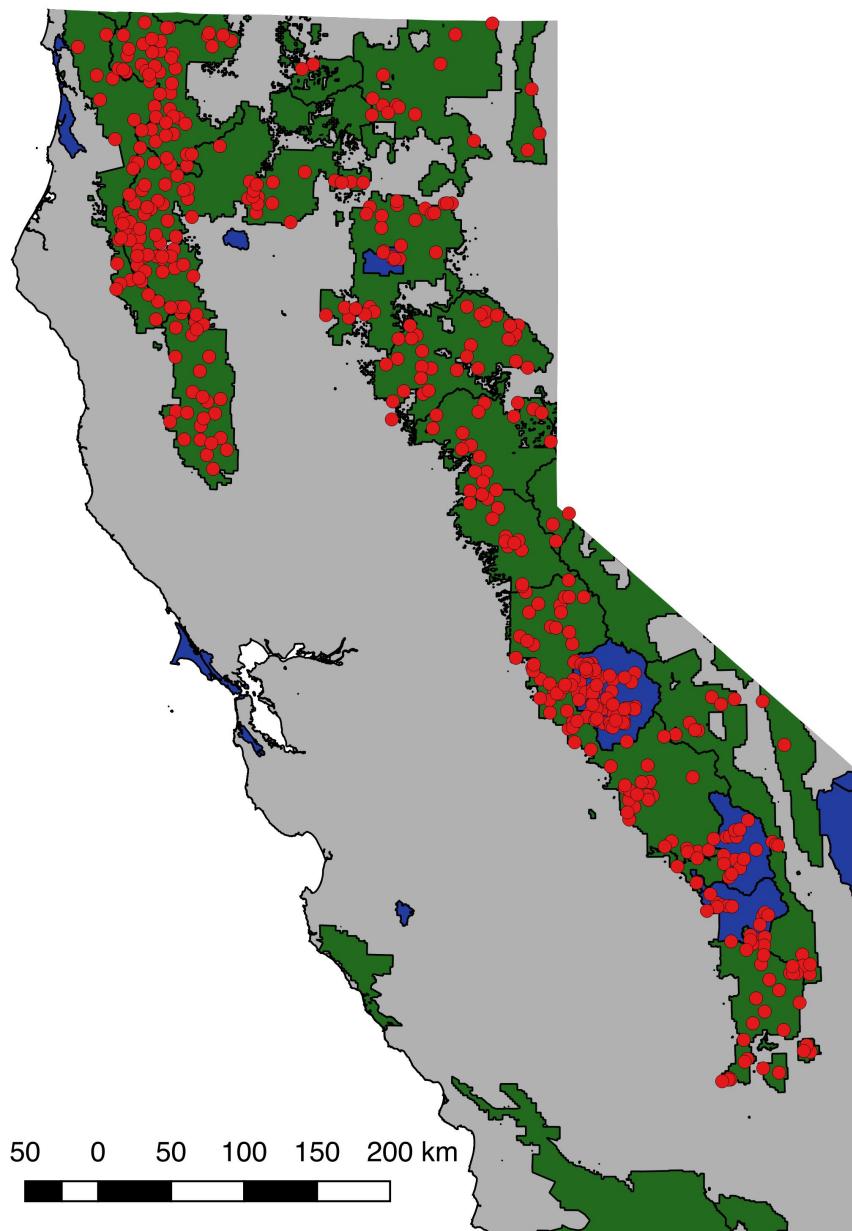
584 **Table 2:** Summary of fire statistics across agency and management class. Fires with agency =
 585 NA were other agencies not among the three principal fire management agencies and with too
 586 few fires to draw meaningful conclusions (e.g. Bureau of Indian Affairs). Agency codes: CDF =
 587 CAL FIRE, USFS = US Forest Service, NPS = US National Park Service. Class codes: SUP =
 588 suppression fires, WFU = Wildland Fire Use fires. Weather variables are the maximum or
 589 minimum daily value over the burn period for a given fire, averaged over all fires in the sample.

agency	class	N	min size (ha)	median size (ha)	max size (ha)	median fire year	mean maximum high temperature	mean maximum burn index	mean maximum low temperature	mean minimum high humidity
CDF	SUP	31	83	828.0	39265	2000	32.7	70.9	14.5	40.0
NPS	SUP	33	84	414.0	24123	1996	27.8	67.7	12.7	36.4
NPS	WFU	54	106	642.5	4143	1996	25.9	74.3	11.7	29.1
USFS	SUP	340	85	1381.5	104038	2003	32.5	69.1	15.4	37.5
USFS	WFU	17	140	928.0	2420	2003	24.9	79.3	10.4	28.2
NA	SUP	2	590	905.0	1220	2010	28.5	76.7	16.2	36.5

590

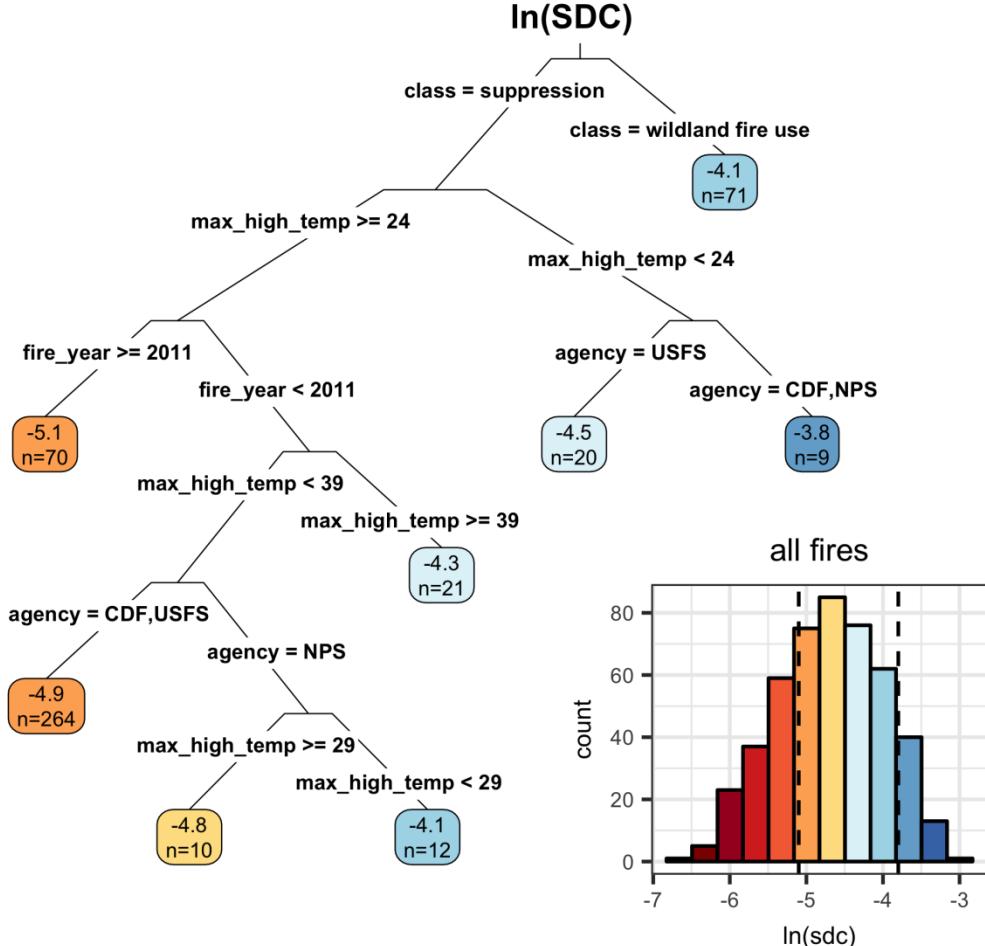
591 **Figure 1:** Locations of the 477 fires in this study (red points). All fires burned within California
592 (gray shading) with at least 50% of the fire perimeter burned in conifer forest on land managed
593 by either the US Forest Service (USFS; green shading) or the US National Park Service (NPS;
594 blue shading), including fires managed by USFS, NPS, and CAL FIRE.

595 [1-column figure]



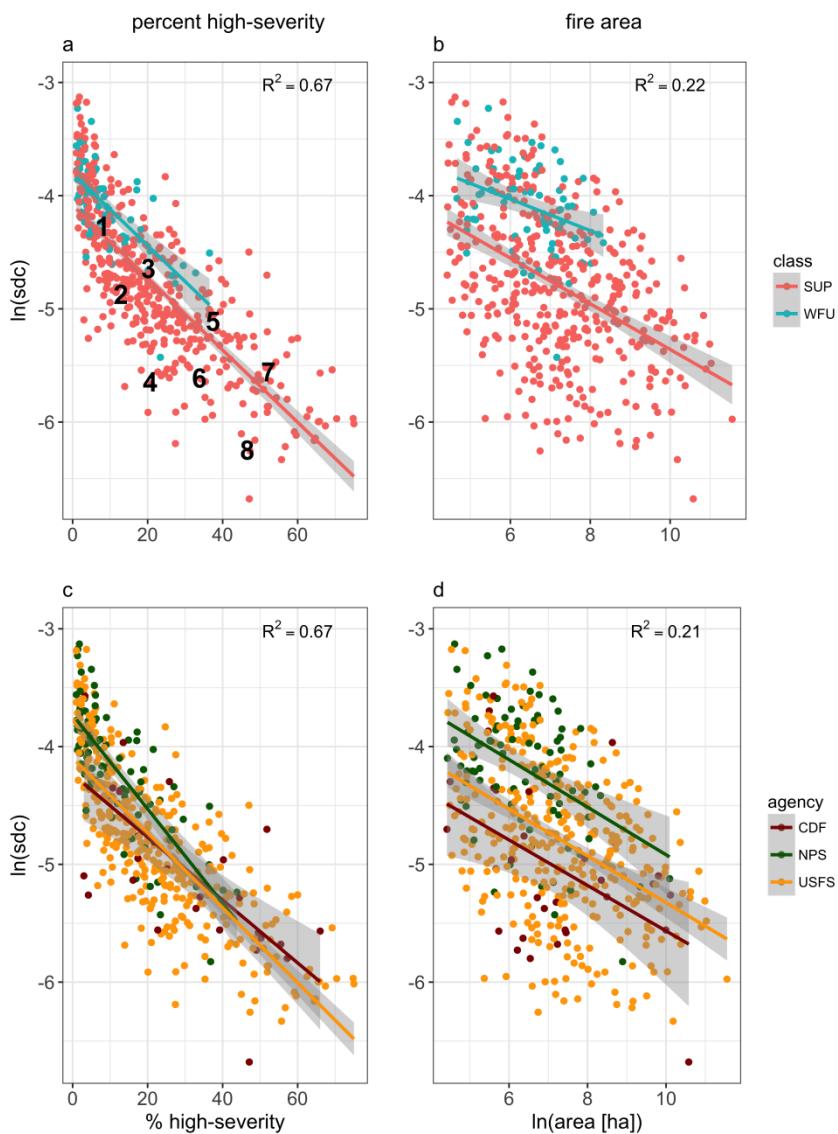
596

597 **Figure 2:** Regression tree based on model 2 (Table 1). Values in ovals are ln-transformed SDC
 598 values, indicating mean ln(SDC) values for fires in a given cluster, with sample size indicated.
 599 Variables are fire management class (suppression, Wildland Fire-Use), maximum daily high
 600 temperature during the burn window (max_high_temp), fire year (1984 through 2015), and fire
 601 management agency (National Park Service *NPS*, US Forest Service *USFS*, or CAL FIRE *CDF*).
 602 Inset figure displays the distribution of ln(SDC) across all 477 fires analyzed in this study, with
 603 dashed lines indicating the range of ln(SDC) values in the ovals. Colors of the ovals correspond
 604 to the histogram bins in the inset figure.
 605 [2-column figure]



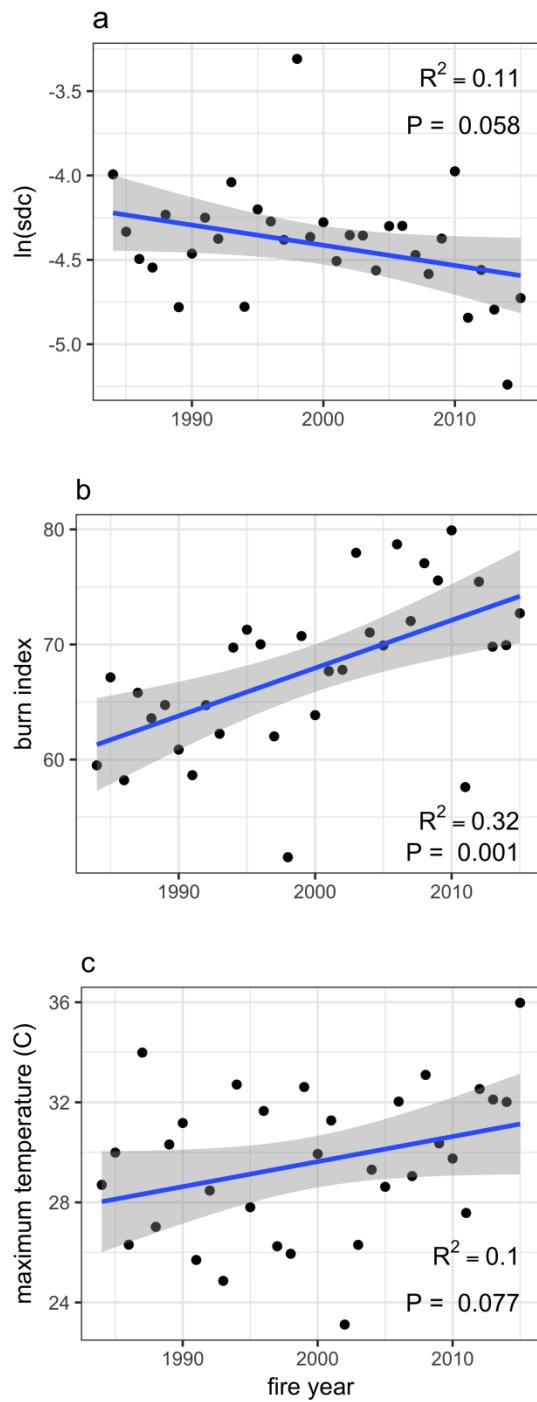
606
 607

608 **Figure 3:** Relationship between $\ln(sdc)$ and percent high-severity (using a 90% basal area
 609 mortality threshold) and fire size (in ha). Fire class (suppression [SUP] vs Wildland Fire Use
 610 [WFU]) and managing agency (CAL FIRE [CDF], US National Park Service [NPS] and US
 611 Forest Service [USFS]) explain differences in $\ln(sdc)$ among fires with otherwise similar percent
 612 high-severity or similar fire size. Numbers in panel (a) correspond to fires used in Figure 6 to
 613 illustrate different stand-replacing patch configurations with similar percent high-severity. Test
 614 statistics for inter-group comparisons given in text.
 615 [1.5 column figure]



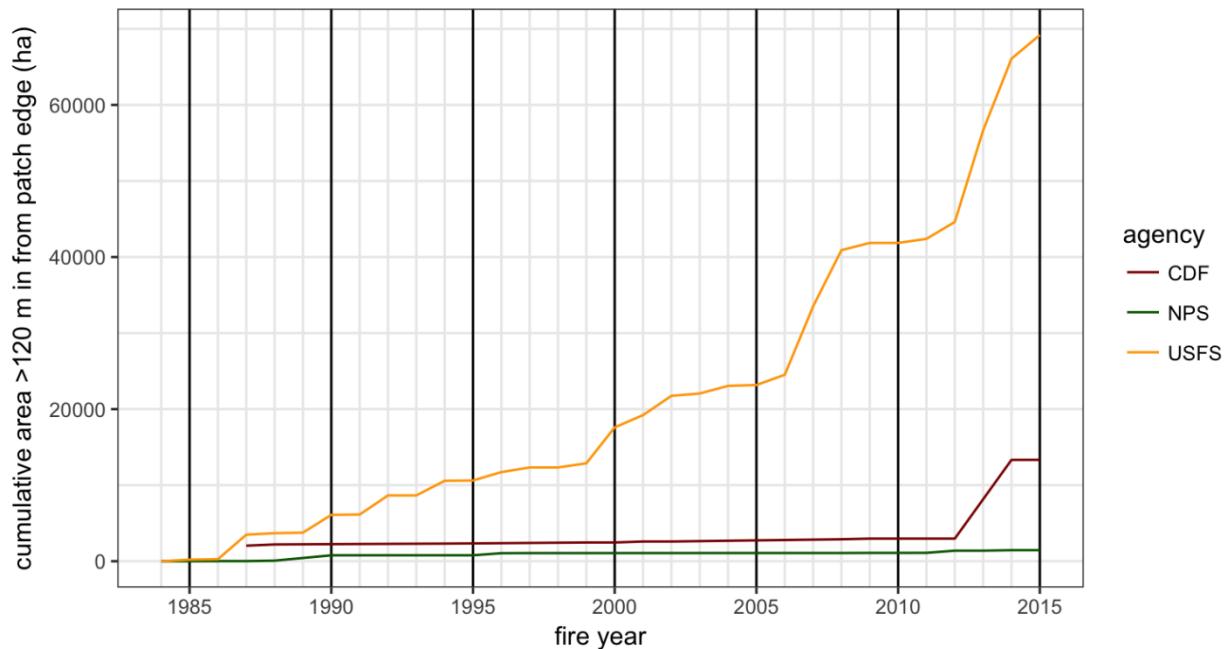
616

617 **Figure 4:** Trends over time in mean annual SDC (a), mean annual maximum burn index during
618 the burn window (b), and mean annual maximum high temperature during the burn window (c).
619 [1 column figure]



620

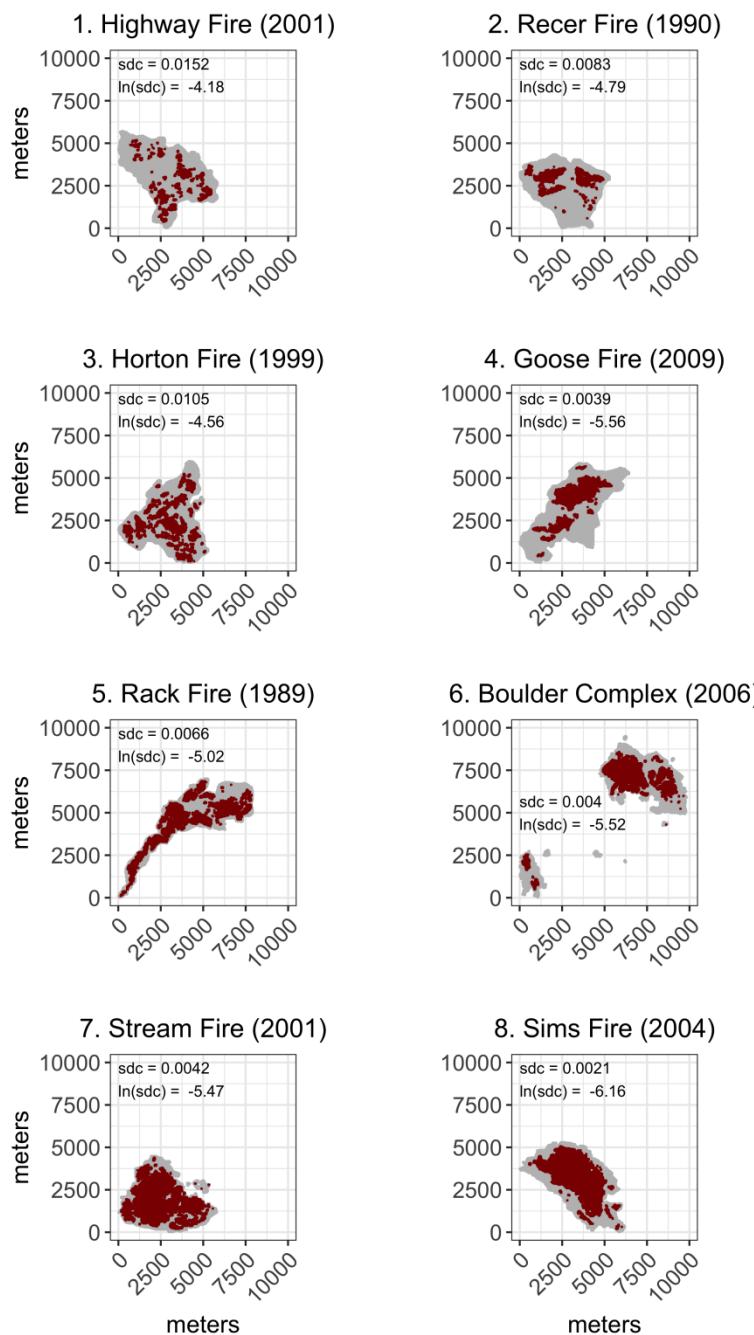
621 **Figure 5:** Increase in cumulative stand-replacing area greater than 120 m from edge since 1984,
622 by agency (CAL FIRE [CDF], US National Park Service [NPS] and US Forest Service [USFS]).
623 “0” represents the value in 1984, as no mapped fires were available before then. In 2015, the
624 cumulative area was 19760 ha for CDF (12.6% of total burned area for CDF), 3499 ha for NPS
625 (3.0% of total burned area for NPS), and 1669378 ha for USFS (7.8% of the total burned area for
626 USFS).



627
628
629
630
631
632
633
634
635

636 **Figure 6:** Examples of SDC for a range of fires. Fires in the same row have similar areas and
637 percent high-severity, corresponding to numbers 1-8 in Figure 3. SDC values are shown on the
638 figure. Fires in the right column have lower SDC values than comparably-sized fires in the left
639 column.

640 [2-column figure]



641

1 **Running Head**

2 Spatial patterns of stand-replacing fire

3 **Title**

4 Changing spatial patterns of stand-replacing fire in California ~~mixed~~-conifer forests

5 **Authors**

6 Jens T. Stevens ^{1*} Brandon M. Collins ² Jay D. Miller ³ Malcolm P. North ^{4,5} Scott L. Stephens ¹

7

8 **Author Affiliations and Addresses**

9 ¹Department of Environmental Science, Policy and Management, University of California,

10 Berkeley, CA, 94720

11 ²Center for Fire Research and Outreach, University of California, Berkeley, CA, 94720

12 ³USDA Forest Service, Pacific Southwest Region, Fire and Aviation Management, McClellan,

13 CA 95652

14 ⁴Department of Plant Sciences, University of California, Davis, CA 95616

15 ⁵USDA Forest Service, Pacific Southwest Research Station, Davis, CA 95618

16 *Corresponding Author. E-mail: stevensjt@berkeley.edu, Telephone: 781-630-3788.

17

18 Original Research Paper

19 **Abstract** [~~372-405~~ words]

20 Stand-replacing fire has profound ecological impacts in ~~mixed~~-conifer forests, yet there is
21 continued uncertainty over how best to describe the scale of stand-replacing effects within
22 individual fires, and how these effects are changing over time. In forests where regeneration
23 following stand-replacing fire depends on seed dispersal from surviving trees, the ~~spatial~~
24 ~~seale-size~~ and ~~pattern-shape~~ of stand-replacing ~~effects is apatches are~~ critical metrics~~s~~ that ~~is-are~~
25 ~~difficult to describe and~~ often overlooked. We used a novel, recently-developed metric that
26 describes the amount of stand-replacing area within a given distance of a live-tree patch edge, in
27 order to compare fires that may be otherwise similar in fire size or the percentage of stand-
28 replacing effects. Specifically, we analyzed 477 fires in California ~~pine, fir, and~~ mixed-conifer
29 forests between 1984 and 2015 and asked whether this metric, the stand-replacing decay
30 coefficient (SDC), has changed over time, whether it is affected by fire management ~~and past~~
31 ~~forest management~~, and how it responds to extreme weather conditions at the time of the fire.
32 Mean annual SDC became smaller over time (significantly so in the Sierra Nevada region),
33 indicating that stand-replacing patches became larger and more regularly shaped. The decrease in
34 SDC was particularly pronounced in the years since 2011. While SDC is correlated with percent
35 high-severity, it is able to distinguish fires of comparable percent high-severity but different
36 spatial pattern, with fires managed for suppression having smaller SDC than fires managed for
37 resource benefit. Similarly, fires managed by the US Forest Service had smaller SDC than fires
38 managed by the National Park Service. Fire weather also played an important role, with higher
39 maximum temperatures generally associated with smaller SDC values. SDC is useful for
40 comparing fires because it is associated with more conventional metrics such as percent high-
41 severity, but also incorporates a measure of regeneration potential – distance to surviving trees at

42 stand-replacement patch edges – which is a biological legacy that directly affects the resilience
43 of forests to increasingly frequent and severe fire disturbances. We estimate that from 1984-2015,
44 over 80,000 ha of forestland burned with stand-replacing effects greater than 120 m in from
45 patch edges, denoting areas vulnerable to extended conifer forest loss due to dispersal limitation.

46 Managing unplanned ignitions for increased wildland fire use under less extreme weather
47 conditions can achieve beneficial “fine-grained” effects of stand-replacing fire where
48 regeneration limitation is less of a concern. Because SDC is a useful single metric to compare
49 fires, we introduce a web application to calculate SDC for any high-severity spatial layer that
50 may be of interest.

51 **Keywords:** California; high-severity; mixed-conifer forests; patch dynamics; stand-replacing;
52 wildland fire

53 **Introduction**

54 In forests, overstory tree mortality from fire is an important ecological process that
55 catalyzes change in forest structure, fuel loads, vegetation diversity and wildlife habitat
56 suitability (Swanson *et al.*, 2011). Tree mortality from fire is a binary process (a tree is top-killed
57 or not), but it is spatially correlated: weather, fuel or topographic conditions that lead to the
58 mortality of one tree also increase the likelihood of mortality for neighboring trees (Collins *et al.*,
59 2007; Thompson and Spies, 2010). When a patch of adjacent trees are all killed by fire, this is
60 termed “stand-replacing fire”. This term is scale-independent – stand-replacing fire can refer to
61 sub-ha stands of ≤ 100 trees, or to many-ha stands of $> 10,000$ trees – but the implications of the
62 spatial scale of stand-replacing fire are profound.

63 Forest resilience, defined as long-term ecosystem persistence and capacity to recover
64 following perturbation (e.g. stand-replacing fire), depends on ecological memory in the form of

65 tree propagules (Holling, 1973; Johnstone *et al.*, 2016). In forests where the dominant tree
66 species have evolved to propagate after being top-killed by fire, (e.g. via basal re-sprouting in
67 oaks (*Quercus spp.*) or serotinous cones in Rocky Mountain lodgepole pine (*Pinus contorta var.*
68 *latifolia*)), resilience is maintained even in large stand-replacing patches. In forests where the
69 dominant tree species lack these adaptations (e.g. many western mixed-conifer forest types), tree
70 propagules generally must arrive via surviving trees on the edges of stand-replacing patches, and
71 the size and shape of these patches becomes critical. Forest resilience is reduced when
72 contiguous stand-replacing patches become larger because tree regeneration towards patch
73 interior is slowed by dispersal limitation, and the likelihood of future stand-replacing fire within
74 these patches increases (Stevens *et al.*, 2014; Chambers *et al.*, 2016; Coppoletta *et al.*, 2016;
75 Johnstone *et al.*, 2016; Welch *et al.*, 2016).

76 What drives much of the concern over stand-replacing fire in mixed-conifer forests is not
77 an intrinsically negative effect of stand-replacing fire, but the potential for large-scale tree
78 regeneration failure and persistent type-conversion (Millar and Stephenson, 2015). As such, there
79 have been numerous attempts to quantify trends in the extent of stand-replacing fire in
80 contemporary wildfires and infer how climate and forest management practices (e.g. historical
81 fire suppression and firefighting tactics) might [drive influence](#) these trends (Miller *et al.*, 2009b;
82 Miller and Safford, 2012; Miller *et al.*, 2012b; Cansler and McKenzie, 2014; Harvey *et al.*,
83 2016b; Picotte *et al.*, 2016).

84 Most efforts to quantify trends in stand-replacing fire rely on interpretation of satellite-
85 based vegetation change indices, particularly the differenced Normalized Burn Ratio (dNBR)
86 (Key and Benson, 2006) and a version of that ratio relativized to pre-fire vegetation cover
87 (RdNBR) (Miller and Thode, 2007). Burn severity (the amount of dominant vegetation killed or

88 consumed by fire within a given area) can be estimated by calibrating this ratio to field-derived
89 data on canopy cover loss from fire, basal area loss from fire, or other composite field indices of
90 burn intensity (Miller *et al.*, 2009a). Modern burn severity classifications transform a continuous
91 variable (e.g. RdNBR) into a discrete variable, generally at a 30-m LANDSAT pixel ~~seale~~
92 ~~resolution~~ (e.g. “low”, “moderate” or “high” severity), based on threshold values associated with
93 particular field conditions (e.g. $\leq 20\%$, 20-70%, or $> 70\%$ basal area mortality). Field validations
94 of post-fire ~~mixed~~-conifer stands mapped as “high-severity”, whether using a 70% or a 90%
95 basal area mortality threshold, indicate these areas generally have $> 95\%$ basal area mortality,
96 with 100% basal area mortality being by far the most common condition greater than 30 m from
97 the edge of a patch mapped as “high-severity” (Miller and Quayle, 2015; Lydersen *et al.*, 2016).
98 Thus, areas of “high-severity fire” mapped in this way are reasonable approximations of “stand-
99 replacing fire”.

100 More recently, the term “mixed-severity-~~fire~~” has become popular to describe individual
101 fires, or characteristic effects of multiple fires (i.e. fire regimes), wherein some fraction of ~~a~~
102 burned area experiences stand-replacing effects delineated in distinct patches (Hessburg *et al.*,
103 2016). While portions ~~of fires a fire's area that are~~ mapped as low or moderate severity still have
104 some tree mortality, individual “mixed-severity fires” are commonly described as those with
105 ~~wherein~~ 20-70% of the fire area ~~is~~-mapped as high-severity ~~using satellite-based classifications~~
106 (Perry *et al.*, 2011). This approach highlights relies upon the concept that patches of stand-
107 replacing fire of *ecologically meaningful size* are those mapped as “high-severity” at 30-m
108 resolution (Collins *et al.*, 2017). Mixed-severity fires generally produce are therefore comprised
109 of discrete patches of stand-replacing fire, eventually filled in by grass, shrubs, or tree
110 regeneration, surrounded by surviving forest that burned at low- to moderate-severity. While the

111 “patchy” nature of mixed-severity fires leads to a wide range of potential stand-replacing patch
112 sizes and shapes, the conventional definition of a mixed-severity fire says nothing about these
113 attributes. Percent high-severity is a useful way to measure fire effects and compare among
114 multiple fires, as it is easily derived and interpreted (Miller *et al.*, 2009b). butHowever, fires
115 where the stand-replacing effects are concentrated in a few large patches are much more
116 susceptible to dispersal limitation of regenerating conifers, and therefore prolonged type
117 conversion to non-forest vegetation, compared to fires with a similar percent high severity but
118 more smaller patches (Crotteau *et al.*, 2013; Kemp *et al.*, 2016; Welch *et al.*, 2016). For instance,
119 the 2013 Rim Fire in California’s Sierra Nevada had a relatively modest proportion of burned
120 area mapped as high severity (~35%) but contained some of the largest contiguous patches of
121 stand-replacing fire found anywhere in the modern record (Lydersen *et al.*, 2017). Thus, there is
122 a need to update previous research on trends in the modern burn severity record by accounting
123 explicitly for the size and shape of stand-replacing patches (Collins *et al.*, 2017).

124 Our objective was to document trends in stand-replacing patch configuration in
125 California’s mixed-conifer forest ecoregion over the past 33 years, using a novel metric
126 developed to describe how much stand-replacing patch area remains with increasing distance
127 inward from patch edges (Collins *et al.*, 2017). The stand-replacing decay coefficient (SDC) is
128 related to fire size, high-severity area, and proportion high-severity, as well as conventional
129 landscape metrics such as patch edge:area ratio (Collins *et al.*, 2017). However, this metric is
130 more biologically relevant than traditional metrics because it explicitly accounts for distance to
131 seed source within stand-replacing patches, and as a single metric it distinguishes among fires
132 that may be similar in terms of fire size or proportion high-severity but differ strongly in
133 aggregate distance to seed source, without needing to specify a specific (and arbitrary) dispersal

134 limitation distance (Collins *et al.*, 2017). Thus SDC can more directly identify fires that are
135 vulnerable to long-term conifer forest loss and potential type-conversion.

136 In this paper, we present analyses that build on previous work investigating trends in burn
137 severity and differences among land management agencies [in California](#) (Miller and Safford,
138 2012; Miller *et al.*, 2012b). More specifically, we include all mapped forest fires >80 ha that
139 occurred [in northwestern California and the Sierra Nevada](#) from 1984 through 2015, which spans
140 two historic multi-year droughts (1987-1992, 2012-2016), to investigate 1) whether fires with
141 different managing agencies and management objectives differed in SDC independently of fire
142 size and proportion high-severity, 2) how average SDC for these fires changed over time, and 3)
143 the role of weather conditions in determining SDC. These results illustrate how a process-based
144 quantification of fire effects can be used to describe changing fire regimes, and this could assist
145 forest managers in developing desired conditions in western US forests that once burned with
146 frequent, low-moderate severity fire regimes.

147 **Methods**

148 Fire behavior and effects are influenced by a multitude of factors, including, but not
149 limited to, past forest management actions, topography, weather and climate. Fires within
150 California are managed primarily by three different agencies; the National Park Service (NPS),
151 US Forest Service (USFS) and the California Department of Forestry and Fire Protection (CAL
152 FIRE). These agencies support very different land management objectives and as such, have
153 different fire management directives. For example, Yosemite, and Sequoia and Kings Canyon
154 National Parks have allowed many lightning-ignited fires to burn under specified conditions to
155 meet resource-management objectives since the early 1970's (van Wagendonk, 2007). Although
156 some National Forests allow some 'resource benefit' fires in more remote, higher-elevation areas,

157 most fires are still suppressed (Stephens and Ruth, 2005). Fires managed by CAL FIRE generally
158 occur at lower elevations in the wildland urban interface (WUI), and therefore are always
159 aggressively suppressed. Beyond potential differences in fire management approaches, the lands
160 these agencies manage have quite different forest management histories. The combined effect of
161 these differences would be expected to result in different fire patterns among these agencies.
162 Because the complex topography of northwestern California can lead to complex patterns of
163 stand-replacing fire (Miller *et al.*, 2012b; Estes *et al.*, 2017), we also considered effects of region
164 (see below).

165 For our analysis, we selected all wildfires in California that burned between 1984 and
166 2015 where the following criteria were met: 1) at least 80 ha in size; 2) predominantly (>50%) in
167 yellow pine (*Pinus ponderosa* or *P. Jeffreyi*), fir (*Abies concolor* or *A. magnifica*) or mixed-
168 conifer forest according to the CALVEG classification scheme (Keeler-Wolf, 2007); 3)
169 occurring in the regions of northwestern California, the southern Cascades, or the Sierra Nevada
170 (see below); 4) predominantly (>50%) on land managed by either the US Forest Service or the
171 US National Park Service; and 5) having a mapped burn-severity classification layer available.
172 These criteria led us to a sample size of 477 fires (Figure 1). For each fire we defined the
173 location of stand-replacing patches as adjacent pixels where the RdNBR exceeded the threshold
174 associated with 90% basal area mortality fire as the set of polygons mapped as >90% basal area
175 mortality using the thresholds in Relative difference Normalized Burn Ratio (RdNBR) from
176 pre-and post-fire LANDSAT imagery (652 for extended assessments and 746 for initial
177 assessments: Miller *et al.*, 2009a; Miller and Quayle, 2015). These patches were converted to
178 polygon shapefiles by Region 5 of the US Forest Service and made available –and available at
179 (<https://www.fs.usda.gov/detail/r5/landmanagement/gis/?cid=stelprd3804878>).

180 We calculated the stand-replacing decay coefficient (SDC) for each fire following the
181 methods of Collins et al. (2017). SDC is defined as:

182

$$P = \frac{1}{10^{SDC * D}} \quad \text{Eq. 1}$$

183 where P is the proportion of the original stand-replacing area in the fire that exceeds a given
184 buffer distance inward from the patch edge (D), and SDC is a free parameter fit by nonlinear
185 least squares estimation that simultaneously describes the size and complexity of stand-replacing
186 area. Smaller SDC values represent larger and/or less complex patches ([Figure A1](#); Collins *et al.*
187 2017). We reasoned that not all edges are biologically equivalent, as outer edges of stand-
188 replacing patches would be more likely to contribute conifer seed into the patch than edges of
189 very small internal “islands” of surviving trees within stand-replacing patches that were mapped
190 as $\leq 90\%$ basal area mortality but most often were mapped as having $> 75\%$ basal area mortality.
191 Therefore we filled in any “islands” of 9 contiguous 30 m pixels (0.81 ha) or smaller, and
192 considered these part of the stand-replacing patch when calculating SDC. The distribution of
193 SDC for our 477 fires was left-skewed so we conducted a natural log (ln) transformation, which
194 improved normality of the data (Collins *et al.*, 2017).

195 For each fire we approximated the weather at the time of the fire using the GridMet
196 database (Abatzoglou, 2013). We identified the start and end dates for each of our 477 fires. In
197 rare cases where the end date was not known ($N=35$), we set the end date to seven days after the
198 start date. We excluded cases where the start date was not known ($N=4$). We then calculated the
199 centroid latitude and longitude coordinate of the high-severity area within a given fire, and
200 downloaded the daily weather estimates from GridMet for the grid cell (4 km) overlapping that
201 centroid during the burn period. Daily estimates were obtained for daily high temperature, low
202 temperature, high relative humidity, and burn index under the assumption that daily extremes are

more likely to influence fire behavior than daily averages (Collins *et al.*, 2007). For each fire we then identified the most extreme fire weather conditions for these four variables during the burn period (maximum high temperature [TMX], maximum low temperature [TMN], minimum high relative humidity [RH], and maximum daily burn index [BI]), and incorporated these variables into our database of fires. Rather than using the lowest relative humidity, we've focused on the minimum high relative humidity in order to capture the recovery (or lack thereof) in relative humidity for a given burn period. Little RH recovery has been associated with greater fire growth potential, and by extension, larger patches of stand-replacing fire (Rothermel, 1991).

To evaluate the influence of fire management class, fire management agency (collectively referred to as “management”), and fire weather/management history/fire management (referred to hereafter as management) on variation in $\ln(\text{SDC})$, we compared a set of candidate models predicting SDC based on all possible combinations of seven variables, using automated model selection implemented in the R package *glmulti* (Calcagno and de Mazancourt, 2010). The candidate models were linear models conducted on the natural log of SDC – $\ln(\text{SDC})$ – which was normally distributed among all fires (Collins *et al.*, 2017). The variables examined were: fire year (1984-2015), fire management class (“class”; fire managed for resource benefit, e.g., wildland fire use [WFU], or suppression [SUP]), management agency (National Park Service [NPS], US Forest Service [USFS], CAL FIRE [CDF]), region (northwestern CA [NW; Shasta Trinity National Forest and all National Forests west from there] and the Southern Cascades/Sierra Nevada [SCSN; all National Forests east of Shasta-Trinity and south to Sequoia and Inyo National Forests]), and the four weather variables (TMX, TMN, RH, BI). We selected the top 5 candidate models on the basis of AIC comparisons, and compared the parameter effect sizes across these models. With parameter effects consistent across the top five candidate models

226 (Table 1), we selected a simple model (model #2) for ~~a-visualization via~~ regression tree analysis
227 using recursive partitioning, implemented in the *rpart* package in R (Therneau *et al.*, 2010).

228 ~~While the linear model comparison approach allowed us to evaluate the important predictor~~
229 ~~variables of ln(SDC) and estimate their parameters, the regression tree analysis identified an~~
230 ~~importance hierarchy of the explanatory variables and provided simple visualization of the model~~
231 ~~structure while identifying important breakpoints within the predictor variables~~ (Therneau *et al.*,
232 2010).

233 We also analyzed temporal trends in ln(SDC) as well as the weather variables TMX and
234 BI using linear regression. There was high inter-annual variability in all of these variables, and a
235 Durbin-Watson test implemented in the R package *car* showed no temporal autocorrelation for
236 any of these variables. ~~Because of this inter-annual variability we also analyzed broader trends in~~
237 ~~these three variables over time by taking a 5-year moving window average of each variable and~~
238 ~~testing for change over time using linear regression. These 5-year averages are inherently~~
239 ~~temporally autocorrelated but can provide a clearer visualization of trends over time (Miller *et al.*,~~
240 ~~2009b)~~. Finally, we calculated the increase over time in cumulative stand-replacing area greater
241 than a specific threshold distance (120 m; Collins *et al.*, 2017) from the patch edge, for each
242 managing agency.

243 Results

244 The best model to explain variation in SDC always included ~~fire~~ management class, ~~fire~~
245 management agency, fire year, and maximum daily high temperature during the burn window,
246 while it never included the minimum daily high humidity (Table 1). Effects of these predictors
247 were consistent: SDC decreased (patches became larger and/or more regular) from NPS to USFS
248 to CDF-managed fires, decreased from WFU fires to SUP fires, decreased over time, and

decreased with increasing maximum high temperatures. Region, maximum low temperature, and maximum burn index were marginal additional predictors in some models (Table 1). The majority of the fires in our study were USFS fires that were actively suppressed; these fires were generally larger and burned under hotter conditions compared to NPS-managed fires or WFU fires (Table 2).

The regression tree analysis indicated that the fire management class was ~~a first-order control on the most important predictor of~~ SDC values, with larger SDC values – associated with smaller and/or more complex patches – for WFU fires (Figure 12). SUP fires generally had smaller SDC values that are associated with larger and/or simpler patches. ~~Fire weather and managing agency were important among SUP fires, with fires burning under cooler temperatures and managed by the National Park Service generally having larger SDC values, and fires burning under warmer temperatures and managed by the US Forest Service generally having smaller SDC values (Figure 2). One exception was a group of fires burning under hot (>39° C) conditions which had larger ln(SDC) values (see Discussion). Among SUP fires where the maximum high temperature during the burn window was less than 24 C, fires managed by the US Forest Service (N=26) had smaller SDC values than fires managed by NPS (N=6) or CDF (N=3), which had ln(SDC) values of -3.8, roughly equivalent to 1.1 ha circular high severity patches (Figure 1, A1).~~ Among SUP fires where the maximum high temperature during the burn window exceeded 24° C, the year of the fire was important, with recent fires occurring during or after 2011 having the smallest ~~mean~~ SDC values of any group of fires. ~~The range of mean ln(SDC) values in the regression tree groups is approximately equivalent to 1 ha circular patches of stand-replacing fire (ln[SDC] = -3.8, SDC = 0.022) for WFU fires, up to 12 ha circular~~

271 patches of stand-replacing fire ($\ln([SDC]) = -5.1$, $SDC = 0.006$) for fires burning since 2011
272 (Figure A2; Collins *et al.*, 2017). equivalent to roughly 12.5 ha circular high severity patches;
273 Figure 1, A1). Among SUP fires before 2011 where the maximum high temperature was greater
274 than 24 C, fires with very high maximum high temperatures (>39 C) surprisingly had larger SDC
275 values (Figure 1), while fires with maximum high temperatures between 24 and 39 C had smaller
276 SDC values if they were managed by CDF or USFS, while if they were managed by the NPS
277 their SDC values depended on temperature, with higher temperatures again leading to smaller
278 SDC values (Figure 1).

279 SDC is related to fire size and percent high-severity because larger fires with more area
280 burning at high-severity will inherently have more area located farther from high-severity patch
281 edges (Collins et al. 2017). However, SDC provides additional information to distinguish fires
282 from each other within a given range of fire size or percent severity. For instance, the reduction
283 in SDC larger SDC values in fires managed by NPS or in fires managed as WFU fires are not just
284 due to these fires being smaller in size or having lower percent high-severity (although these
285 effects do exist). Rather, within a given fire size or percent high-severity range, agency and class
286 still influence SDC (Figure 2). In a model of SDC conditional on class (SUP vs WFU) and either
287 percent high-severity or fire size, class has a significant marginal effect on SDC after accounting
288 for percent severity ($t = 5.35$, $P < 0.001$; Figure 32a) and size ($t = 7.92$, $P < 0.001$; Figure 32b).
289 In a model of SDC conditional on agency and either percent high-severity or fire size, agency
290 also has a significant effect on SDC after accounting for these variables (Figure 3c,d), with NPS
291 distinguishable from both USFS ($t = 5.54$, $P < 0.001$ after accounting for percent high-severity; t
292 = 7.07, $P < 0.001$ after accounting for fire size) and CDF ($t = 3.03$, $P = 0.003$ after accounting for
293 percent high-severity; $t = 5.78$, $P < 0.001$ after accounting for fire size), while the latter two are

294 indistinguishable from each other ($t = 0.16$, $P = 0.877$) after accounting for percent high-severity,
295 and marginally significantly different from each other ($t = 1.925$, $P = 0.055$) after accounting for
296 fire size).

297 Although fire management class and agency are clearly related to SDC values, the
298 relationship between fire year, weather during the fire, and SDC is more complex. Average
299 annual SDC decreased over time (Figure 4a), at a rate that was marginally significant ~~for both~~
300 ~~the individual year averages~~ ($R^2 = 0.11$, $t = 1.97$, $P = 0.058$)~~and the five year moving averages~~
301 ($R^2 = 0.14$, $t = 2.08$, $P = 0.047$). The maximum average daily burn index during the time of a fire
302 increased significantly over time (Figure 4b-d), ~~significantly both for individual year averages (:~~
303 $R^2 = 0.32$, $t = 3.80$, $P = 0.001$)~~and for the five year moving average ($R^2 = 0.69$, $t = 7.60$, $P <$~~
304 ~~0.001~~). Similarly, the average annual maximum high temperature, ~~averaged across all fires~~
305 ~~within a given year, during the time of a fire~~ increased over time from 1984-2015 (Figure 4c), a
306 trend that was ~~significant for the five year moving average ($R^2 = 0.29$, $t = 3.29$, $P = .003$)~~ and
307 marginally significant for individual year averages ($R^2 = 0.010$, $t = 1.83$, $P = 0.077$). However,
308 while four of the six lowest average SDC values in the 31-year time period occurred between
309 2011 and 2015, only one of the six highest average burn index years and two of the six highest
310 average temperature years occurred in this same period (Figure 4a). Consistent with previous
311 work showing regional differences in stand-replacing effects, we also found a significant
312 decrease in annual average SDC over time in the Southern Cascades/Sierra Nevada ($R^2 = 0.12$, t
313 $= 2.05$, $P = .049$) but not in northwestern California ($R^2 = 0.004$, $t = 0.32$, $P = .750$) (Figure A3);
314 ~~however neither trend was significant when the 5 year moving average was evaluated, although~~
315 ~~northwestern California was marginally significant ($R^2 = 0.046$, $t = 1.14$, $P = .264$ for SCSN; R^2~~
316 ~~= 0.16, $t = 2.01$, $P = .057$ for NW)~~ (Figure A3b).

317 SDC can be used to calculate the proportion of stand-replacing effects in a given fire
318 greater than a critical dispersal distance threshold in from the patch edge. This proportion can
319 thus be used to calculate the area in a given fire that will likely be void of substantive natural
320 conifer regeneration. When we calculated this area of potential “forest loss” for all fires in our
321 study using a common dispersal distance threshold of 120 m (Collins *et al.*, 2017), we found that
322 over 80,000 ha of stand-replacing fire in the study area since 1984 occurred more than 120 m
323 from a patch edge, with most of that area concentrated in fires managed by USFS (Figure 54).
324 This area represents 12.6% of total area burned for CDF fires, 7.8% of total area burned for
325 USFS fires and 3.0% of total area burned for NPS fires (Figure 5).

326 Discussion

327 The SDC tended towards smaller values (e.g. larger and less complex high-severity
328 patches) over time in fires managed for suppression, and on landscapes with a longer history of
329 suppressing almost all fires (e.g. USFS) (Stephens and Ruth, 2005; van Wagtendonk, 2007;
330 Meyer, 2015). These broad trends are generally consistent with previous work documenting
331 increases in the percentage of stand-replacing effects within a fire over time, and on USFS land
332 rather than NPS land in the Sierra Nevada (Miller *et al.*, 2009b; Miller *et al.*, 2012a; Miller and
333 Safford, 2012). However, in corroborating this previous work, our results provide important
334 additional information, because for the first time we are describing quantifying changes in the spatial
335 patterns of stand-replacing fire that directly reflect changes in post-fire regeneration potential
336 (e.g. distance to seed source) and potential loss of conifer forest, at least in the near term.

337 The advantage of SDC over metrics such as percent high-severity is that fires with similar
338 percentages can have dramatically different patch sizes that affect ecosystem recovery SDC
339 values (Figure 23). This can be visualized in Figure 65, which illustrates a set of comparison

340 fires with similar percent high-severity and similar fire area, but different spatial patterns and
341 SDC values. SDC is a useful addition to this existing set of metrics because it is a single metric,
342 comparable across a large number of fires, that simultaneously accounts for covariation in
343 percent high-severity, area burned at high-severity, edge:area ratio of high-severity patches, and
344 other metrics that are correlated with, but do not directly measure, the potential for dispersal
345 limitation (Collins *et al.*, 2017). It is this dispersal limitation and resultant lags in forest
346 regeneration, rather than percentages of an area burning at high-severity *per se*, that may
347 contribute to potential forest loss and establishment of alternative stable states. (Millar and
348 Stephenson, 2015; Coppoletta *et al.*, 2016; Harvey *et al.*, 2016a; Johnstone *et al.*, 2016). This
349 potential is only exacerbated by anticipated changes in regional climate, ~~and~~ fire frequency and
350 area burned (Littell *et al.*, 2009; Westerling *et al.*, 2011; Parks *et al.*, 2017), which further
351 increases the likelihood of high-severity fires re-burning in short succession.

352 Weather and fuels can strongly influence fire severity and area burned (Safford *et al.*,
353 2012; Collins, 2014; Lydersen *et al.*, 2014; Parks *et al.*, 2015), and our results ~~corroborate~~
354 ~~this suggest that this is the case~~ for spatial patterns of stand-replacing fire as well (e.g., Cansler
355 and McKenzie, 2014). Under more moderate weather conditions, fire effects tended to be within
356 the range of historical variability for California ~~mixed~~-conifer forests – smaller, more irregular
357 patches of stand-replacing fire generally < 2ha (Safford and Stevens, 2017) – ~~under more~~
358 ~~moderate weather conditions~~. Maximum daily high temperature during the burn period was an
359 important factor and fires burning under cooler conditions generally had SDC values around 4.1,
360 associated with an average patch size of around 2 ha (Figure 42, Figure A1). Although “fuels”
361 ~~are somewhat captured by our management class variable by their indirect connection with forest~~
362 ~~management history, relevant fuel characterizations are largely lacking the spatial and temporal~~

363 resolution that are available for weather variables. As such, it is not surprising that our analyses,
364 and several other studies (e.g., Abatzoglou and Williams, 2016), consistently identify greater
365 relative importance of weather and climate variables over fuels. We were surprised that burn
366 index was not identified as an important predictor of SDC. This could be due to inaccuracies
367 related to downscaling burn index in the climate data, or because the maximum burn index
368 during a burn window may be less relevant to stand-replacing fire than the duration of periods
369 with high burn index. Further work is needed that could examine more sophisticated
370 representations of weather tied specifically to the period and location of stand-replacing patches
371 with small SDC values.

372 Although management class emerged as the first order most important control over SDC
373 (Figure 42), this also reflects the influence of weather to some degree because decisions on
374 whether to manage fires are based partly on weather conditions (North *et al.*, 2012; Meyer, 2015).
375 Our dataset supports this, as “wildland fire use” fires tended to burn under cooler maximum high
376 temperatures than fires managed for suppression, regardless of agency (Table 2). Similarly,
377 fires managed for suppression in the NPS tend to have cooler maximum high temperatures than
378 fires on USFS land, even when suppression is the management objective (Table 2), which might
379 reflect the higher elevation of the three National Parks in the Sierra Nevada relative to the
380 majority of National Forest land (Figure 1). However, to the extent that geographic differences in
381 management agencies are associated with differences in weather, these results suggest there
382 may be opportunities for increased fire use on Forest Service land during the spring and fall,
383 when temperatures are lower, in order to that would more closely mimic the fine-grained stand-
384 replacement patterns evident on National Parks land (Figure 1).

385 Although the influence of “fuels” on SDC is may be indirectly are somewhat
386 capturedrepresented by our management class variable by their indirectand its connection with
387 forest management history, relevant fuel characterizations are largely lacking the spatial and
388 temporal resolution that are available for weather variables. Despite this limitationWhile we do
389 not account for fuels directly in our analysis, several lines of evidence suggest that increased fuel
390 loads are associated with smaller SDC values. The trend towards smaller SDC values over time
391 may reflect the effect of fire suppression and associated fuel accumulation. However, but
392 California also experienced a severe four-year drought from the winter 2011-2012 through the
393 winter 2014-2015 (Young *et al.*, 2017), which likely had an effect on this trend. The years from
394 2011-2015 had four of the six lowest mean SDC values of any year since 1984, and while
395 maximum temperature and burn index increased over this time period, only two of those years
396 (2012 and 2015) were among the six highest maximum temperature years based on burn-period
397 temperatures, and only one (2012) was among the six highest burn index years (Figure 43). Our
398 regression tree analysis identifies 2011 as a threshold year, with fires occurring on or after that
399 year having the smallest mean SDC value of any cluster in the tree, after controlling for the
400 effect of temperature (Figure 23). Furthermore, smaller SDC values for fires managed by the
401 USFS compared to the NPS after controlling for weather (Table 1) may indicate a longer
402 history of fire suppression on USFS lands (Miller *et al.*, 2012a), which have a broader array of
403 constraints when considering how to manage ignitions (van Wagtendonk, 2007).

404 Topography is also an important control over fire effects (Taylor and Skinner, 2003;
405 Lydersen *et al.*, 2014; Harris and Taylor, 2015; Estes *et al.*, 2017). In areas with high
406 topographic complexity, patterns of stand-replacing fire may be less responsive to variation in
407 fuels or weather (Miller *et al.*, 2012b). We found a seemingly counterintuitive result in our

408 regression tree analysis where fires with a maximum high temperature greater than or equal to
409 39°C had smaller_larger SDC values (N=18, Figure 42). Every one of these fires, however,
410 occurred in the northwestern part of California centered around the Klamath Mountains, with a
411 majority (N=10) occurring in 1987, a particularly warm year (Figure 34) with widespread
412 lightning fire activity in this region. Temperature inversions within the topographically complex
413 Klamath region are common when summer high-pressure systems setup over the region. The
414 inversions have been documented to trap smoke from wildland fire in valleys for weeks,
415 reducing solar insolation and daytime maximum temperatures in valleys relative to nearby
416 ridgetops (Robock, 1988). As a result daytime fire activity is suppressed in some areas, even in
417 particularly warm years like 1987, which can moderate fire behavior and reduce stand-replacing
418 effects (Robock, 1988; Estes *et al.*, 2017). The topographic complexity of the Klamath
419 Mountains may also explain why we did not see a significant decrease in SDC over time in that
420 region, but we did see a significant decrease in the Sierra Nevada (Miller and Safford, 2012;
421 Miller *et al.*, 2012b).

422 While it is difficult to ascribe strict causality to the observed trends in SDC, multiple
423 lines of evidence suggest that primary drivers are changes in weather and fuels. The ongoing
424 increase in both extreme weather frequency and fuel accumulation across many forested
425 landscapes (Collins, 2014; Millar and Stephenson, 2015; Safford and Stevens, 2017) are likely
426 contributing to larger and more regular stand-replacing patches. As such, the occurrence of so-
427 called “mega-fires”, where fire behavior and effects exceed the range of variability previously
428 observed, is expected to continue to increase over time unless substantive fuel reduction and
429 forest restoration efforts are implemented in the appropriate forest types (Stephens *et al.*, 2014b).

430 Low SDC values appear to be aare good indicatorcharacteristic of “mega-fires”, and
431 their incidence appears to be on the rise. These fires contribute disproportionately to the
432 cumulative area of forest loss where a dispersal distance threshold of 120 m is exceeded (Figure
433 54). For example, over the 32 years from 1984-2015, 20 fires have had an SDC smaller than
434 0.0026. Of these 20 fires, half (10) have occurred in the 9 years since 2007, including some well-
435 known recent fires widely considered to be “mega-fires”, including the 2007 Moonlight Fire
436 (Stephens *et al.*, 2014a), the 2013 Rim Fire (Lydersen *et al.*, 2014), and the 2014 King Fire
437 (Jones *et al.*, 2016), which has the smallest SDC of any of the 477 fires studied (SDC = 0.0013;
438 $\ln(\text{SDC}) = -6.64$). These fires contribute disproportionately to the cumulative area of forest loss
439 where a dispersal distance threshold of 120 m is exceeded (Figure 4). Because SDC is a useful
440 single metric to compare fires, we have createdintroduce a web application to calculate SDC for
441 any high-severity spatial layer that may be of interest to a researcher or manager
442 (stevensjt.shinyapps.io/sdc_app). This ‘app’ allows a user to upload a shapefile of stand-
443 replacing patches in a metric coordinate system and compare a particular fire against the SDC
444 values of all 477 fires analyzed in this paper. This tool may also allowS for a statistical
445 comparison of fires from other regions outside of California that are thought to be at risk for
446 regeneration failure within stand-replacing patches (e.g., Chambers *et al.*, 2016)

447 Fires with larger more desirable SDC values indicative of smaller circular patches of 10
448 ha or less (e.g. SDC > 0.0067; $\ln(\text{SDC}) = -5$; Figure 34, 56A2) suggest a way forward for fire
449 management that incorporates some of the benefits of stand-replacing fire while not
450 compromising long-term forest resilience (Meyer, 2015). Managed wWildfires that burn under
451 moderate fire weather conditions or landscapes with a past history of fire use or other fuel
452 managementare managed by agencies with a longer history of fire use are much more likely to

453 have smaller-larger SDC values, even if their percentage of high-severity effects are in the 20-
454 40% range (Figure 32). This is consistent with a large and developing body of literature
455 suggesting that there are opportunities for increased use of fire, in concert with mechanical fuels
456 reduction in some instances, during periods of time where rapid fire spread is not likely
457 (Stephens *et al.*, 2013; Millar and Stephenson, 2015; North *et al.*, 2015; Stephens *et al.*, 2016).
458 There are many barriers to the increased use of fire, but current trends in stand replacement
459 spatial patterns mean that the alternative could be increasingly large dead tree patches where
460 forest regeneration is delayed for extended periods of time.

461 Acknowledgments

462 This work was also supported by a research partnership between the US Forest Service
463 Pacific Southwest Research Station and UC Berkeley College of Natural Resources (project no.
464 16-JV-11272167-063). Zack Steel and Sean Parks provided helpful comments on an earlier
465 version of this manuscript.

466 Literature Cited

467
468 Abatzoglou, J.T., 2013. Development of gridded surface meteorological data for ecological
469 applications and modelling. International Journal of Climatology 33, 121-131.
470 Calcagno, V., de Mazancourt, C., 2010. glmulti: an R package for easy automated model
471 selection with (generalized) linear models. Journal of Statistical Software 34, 1-29.
472 Cansler, C.A., McKenzie, D., 2014. Climate, fire size, and biophysical setting control fire
473 severity and spatial pattern in the northern Cascade Range, USA. Ecol. Appl. 24, 1037-1056.
474 Chambers, M.E., Fornwalt, P.J., Malone, S.L., Battaglia, M.A., 2016. Patterns of conifer
475 regeneration following high severity wildfire in ponderosa pine – dominated forests of the
476 Colorado Front Range. For. Ecol. Manag. 378, 57-67.

- 477 Collins, B.M., 2014. Fire weather and large fire potential in the northern Sierra Nevada. Agric.
478 For. Meteorol. 189–190, 30-35.
- 479 Collins, B.M., Kelly, M., van Wagtendonk, J.W., Stephens, S.L., 2007. Spatial patterns of large
480 natural fires in Sierra Nevada wilderness areas. Landsc. Ecol. 22, 545-557.
- 481 Collins, B.M., Stevens, J.T., Miller, J.D., Stephens, S.L., Brown, P.M., North, M.P., 2017.
482 Alternative characterization of forest fire regimes: incorporating spatial patterns. Landsc. Ecol.
483 32, 1543-1552.
- 484 Coppoletta, M., Merriam, K.E., Collins, B.M., 2016. Post-fire vegetation and fuel development
485 influences fire severity patterns in reburns. Ecol. Appl. 26, 686-699.
- 486 Crotteau, J.S., Morgan Varner Iii, J., Ritchie, M.W., 2013. Post-fire regeneration across a fire
487 severity gradient in the southern Cascades. For. Ecol. Manag. 287, 103-112.
- 488 Estes, B.L., Knapp, E.E., Skinner, C.N., Miller, J.D., Preisler, H.K., 2017. Factors influencing
489 fire severity under moderate burning conditions in the Klamath Mountains, northern California,
490 USA. Ecosphere 8, e01794-n/a.
- 491 Harris, L., Taylor, A.H., 2015. Topography, fuels and fire exclusion drive fire severity of the
492 Rim Fire in an old-growth mixed- conifer forest, Yosemite National Park, USA. Ecosystems 18,
493 1192-1208.
- 494 Harvey, B.J., Donato, D.C., Turner, M.G., 2016a. Burn me twice, shame on who? Interactions
495 between successive forest fires across a temperate mountain region. Ecology 97, 2272-2282.
- 496 Harvey, B.J., Donato, D.C., Turner, M.G., 2016b. Drivers and trends in landscape patterns of
497 stand-replacing fire in forests of the US Northern Rocky Mountains (1984–2010). Landsc. Ecol.
498 31, 2367-2383.

- 499 Hessburg, P.F., Spies, T.A., Perry, D.A., Skinner, C.N., Taylor, A.H., Brown, P.M., Stephens,
500 S.L., Larson, A.J., Churchill, D.J., Povak, N.A., Singleton, P.H., McComb, B., Zielinski, W.J.,
501 Collins, B.M., Salter, R.B., Keane, J.J., Franklin, J.F., Riegel, G., 2016. Tamm Review:
502 Management of mixed-severity fire regime forests in Oregon, Washington, and Northern
503 California. *For. Ecol. Manag.* 366, 221-250.
- 504 Holling, C.S., 1973. Resilience and stability of ecological systems. *Annu. Rev. Ecol. Syst.* 4, 1-
505 23.
- 506 Johnstone, J.F., Allen, C.D., Franklin, J.F., Frelich, L.E., Harvey, B.J., Higuera, P.E., Mack,
507 M.C., Meentemeyer, R.K., Metz, M.R., Perry, G.L.W., Schoennagel, T., Turner, M.G., 2016.
508 Changing disturbance regimes, ecological memory, and forest resilience. *Frontiers in Ecology*
509 and the Environment
- 510 Jones, G.M., Gutiérrez, R.J., Tempel, D.J., Whitmore, S.A., Berigan, W.J., Peery, M.Z., 2016.
511 Megafires: an emerging threat to old-forest species. *Frontiers in Ecology and the Environment* 14,
512 300-306.
- 513 Keeler-Wolf, T., 2007. The history of vegetation classification and mapping in California. In:
514 Barbour, M.G., Keeler-Wolf, T., Schoenherr, A.A. (Eds.), *Terrestrial vegetation of California*.
515 University of California Press, Berkeley, CA, pp. 1-42.
- 516 Kemp, K.B., Higuera, P.E., Morgan, P., 2016. Fire legacies impact conifer regeneration across
517 environmental gradients in the U.S. northern Rockies. *Landsc. Ecol.* 31, 619-636.
- 518 Key, C.H., Benson, N.C., 2006. Landscape assessment: remote sensing of severity, the
519 Normalized Burn Ratio. In: Lutes, D.C. (Ed.), *FIREMON: Fire effects monitoring and inventory*
520 system Ogden, Utah: USDA Forest Service, Rocky Mountain Res. Station, Fort Collins,
521 Colorado, USA, pp. LA25 - LA41.

- 522 Littell, J.S., McKenzie, D., Peterson, D.L., Westerling, A.L., 2009. Climate and wildfire area
523 burned in western U.S. ecoprovinces, 1916–2003. *Ecol. Appl.* 19, 1003-1021.
- 524 Lydersen, J.M., Collins, B.M., Brooks, M.L., Matchett, J.R., Shive, K.L., Povak, N.A., Smith,
525 D.F., 2017. Evidence of fuels management and fire weather influencing fire severity in an
526 extreme fire event. *Ecol. Appl.* *in press*.
- 527 Lydersen, J.M., Collins, B.M., Miller, J.D., Fry, D.L., Stephens, S.L., 2016. Relating fire-caused
528 change in forest structure to remotely sensed estimates of fire severity. *Fire Ecology* 12, 99-116.
- 529 Lydersen, J.M., North, M.P., Collins, B.M., 2014. Severity of an uncharacteristically large
530 wildfire, the Rim Fire, in forests with relatively restored frequent fire regimes. *For. Ecol. Manag.*
531 328, 326-334.
- 532 Meyer, M.D., 2015. Forest Fire Severity Patterns of Resource Objective Wildfires in the
533 Southern Sierra Nevada. *Journal of Forestry* 113, 49-56.
- 534 Millar, C.I., Stephenson, N.L., 2015. Temperate forest health in an era of emerging
535 megadisturbance. *Science* 349, 823-826.
- 536 Miller, J.D., Collins, B.M., Lutz, J.A., Stephens, S.L., van Wagendonk, J.W., Yasuda, D.A.,
537 2012a. Differences in wildfires among ecoregions and land management agencies in the Sierra
538 Nevada region, California, USA. *Ecosphere* 3, art80.
- 539 Miller, J.D., Knapp, E.E., Key, C.H., Skinner, C.N., Isbell, C.J., Creasy, R.M., Sherlock, J.W.,
540 2009a. Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to
541 three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA.
542 *Remote Sens. Environ.* 113, 645-656.
- 543 Miller, J.D., Quayle, B., 2015. Calibration and validation of immediate post-fire satellite derived
544 data to three severity metrics. *Fire Ecology* 11, 12-30.

- 545 Miller, J.D., Safford, H., 2012. Trends in wildfire severity 1984-2010 in the Sierra Nevada,
546 Modoc Plateau and southern Cascades, California, USA. *Fire Ecology* 8, 41-57.
- 547 Miller, J.D., Safford, H.D., Crimmins, M., Thode, A.E., 2009b. Quantitative evidence for
548 increasing forest fire severity in the Sierra Nevada and southern Cascade Mountains, California
549 and Nevada, USA. *Ecosystems* 12, 16-32.
- 550 Miller, J.D., Skinner, C.N., Safford, H.D., Knapp, E.E., Ramirez, C.M., 2012b. Trends and
551 causes of severity, size, and number of fires in northwestern California, USA. *Ecol. Appl.* 22,
552 184-203.
- 553 Miller, J.D., Thode, A.E., 2007. Quantifying burn severity in a heterogeneous landscape with a
554 relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sens. Environ.* 109, 66-80.
- 555 North, M., Collins, B.M., Stephens, S., 2012. Using fire to increase the scale, benefits, and future
556 maintenance of fuels treatments. *Journal of Forestry* 110, 392-401.
- 557 North, M.P., Stephens, S.L., Collins, B.M., Agee, J.K., Aplet, G., Franklin, J.F., Fulé, P.Z., 2015.
558 Reform forest fire management. *Science* 349, 1280-1281.
- 559 Parks, S.A., Holsinger, L.M., Miller, C., Nelson, C.R., 2015. Wildland fire as a self-regulating
560 mechanism: the role of previous burns and weather in limiting fire progression. *Ecol. Appl.* 25,
561 1478-1492.
- 562 Parks, S.A., Holsinger, L.M., Miller, C., Parisien, M.-A., 2017. Analog-based fire regime and
563 vegetation shifts in mountainous regions of the western US. *Ecography* In Press.
- 564 Perry, D.A., Hessburg, P.F., Skinner, C.N., Spies, T.A., Stephens, S.L., Taylor, A.H., Franklin,
565 J.F., McComb, B., Riegel, G., 2011. The ecology of mixed severity fire regimes in Washington,
566 Oregon, and northern California. *For. Ecol. Manag.* 262, 703-717.

- 567 Picotte, J.J., Peterson, B., Meier, G., Howard, S.M., 2016. 1984–2010 trends in fire burn severity
568 and area for the conterminous US. *Int. J. Wildland Fire* 25, 413-420.
- 569 Robock, A., 1988. Enhancement of Surface Cooling Due to Forest Fire Smoke. *Science* 242,
570 911-913.
- 571 Rothermel, R.C., 1991. Predicting behavior and size of crown fires in the Northern Rocky
572 Mountains. In, USDA Forest Service, Intermountain Research Station.
- 573 Safford, H.D., Stevens, J.T., 2017. Natural Range of Variation (NRV) for yellow pine and mixed
574 conifer forests in the Sierra Nevada, southern Cascades, and Modoc and Inyo National Forests,
575 California, USA. In. USDA Forest Service, Pacific Southwest Research Station. General
576 Technical Report PSW-GTR-256, Albany, CA.
- 577 Safford, H.D., Stevens, J.T., Merriam, K., Meyer, M.D., Latimer, A.M., 2012. Fuel treatment
578 effectiveness in California yellow pine and mixed conifer forests. *For. Ecol. Manag.* 274, 17-28.
- 579 Stephens, S.L., Agee, J.K., Fulé, P.Z., North, M.P., Romme, W.H., Swetnam, T.W., Turner,
580 M.G., 2013. Managing forests and fire in changing climates. *Science* 342, 41-42.
- 581 Stephens, S.L., Bigelow, S.W., Burnett, R.D., Collins, B.M., Gallagher, C.V., Keane, J., Kelt,
582 D.A., North, M.P., Roberts, L.J., Stine, P.A., Van Vuren, D.H., 2014a. California spotted owl,
583 songbird, and small mammal responses to landscape fuel treatments. *Bioscience*.
- 584 Stephens, S.L., Burrows, N., Buyantuyev, A., Gray, R.W., Keane, R.E., Kubian, R., Liu, S.,
585 Seijo, F., Shu, L., Tolhurst, K.G., van Wagtendonk, J.W., 2014b. Temperate and boreal forest
586 mega-fires: characteristics and challenges. *Frontiers in Ecology and the Environment* 12, 115-
587 122.
- 588 Stephens, S.L., Collins, B.M., Biber, E., Fulé, P.Z., 2016. U.S. federal fire and forest policy:
589 emphasizing resilience in dry forests. *Ecosphere* 7, e01584-n/a.

- 590 Stephens, S.L., Ruth, L.W., 2005. Federal forest-fire policy in the United States. *Ecol. Appl.* 15,
591 532-542.
- 592 Stevens, J.T., Safford, H.D., Latimer, A.M., 2014. Wildfire-contingent effects of fuel treatments
593 can promote ecological resilience in seasonally dry conifer forests. *Can. J. For. Res.* 44, 843-854.
- 594 Swanson, M.E., Franklin, J.F., Beschta, R.L., Crisafulli, C.M., DellaSala, D.A., Hutto, R.L.,
595 Lindenmayer, D.B., Swanson, F.J., 2011. The forgotten stage of forest succession: early-
596 successional ecosystems on forest sites. *Frontiers in Ecology and the Environment* 9, 117-125.
- 597 Taylor, A.H., Skinner, C.N., 2003. Spatial patterns and controls on historical fire regimes and
598 forest structure in the Klamath Mountains. *Ecol. Appl.* 13, 704-719.
- 599 Therneau, T.M., Atkinson, B., Ripley, B., 2010. rpart: Recursive partitioning. R package version
600 3, 1-46.
- 601 Thompson, J., Spies, T., 2010. Factors associated with crown damage following recurring
602 mixed-severity wildfires and post-fire management in southwestern Oregon. *Landsc. Ecol.* 25,
603 775-789.
- 604 van Wagendonk, J.W., 2007. The history and evolution of wildland fire use. *Fire Ecology* 3, 3-
605 17.
- 606 Welch, K.R., Safford, H.D., Young, T.P., 2016. Predicting conifer establishment post wildfire in
607 mixed conifer forests of the North American Mediterranean-climate zone. *Ecosphere* 7, e01609-
608 n/a.
- 609 Westerling, A.L., Bryant, B.P., Preisler, H.K., Holmes, T.P., Hidalgo, H.G., Das, T., Shrestha,
610 S.R., 2011. Climate change and growth scenarios for California wildfire. *Clim. Change* 109,
611 S445-S463.

- 612 Young, D.J.N., Stevens, J.T., Earles, J.M., Moore, J., Ellis, A., Jirka, A.L., Latimer, A.M., 2017.
- 613 Long-term climate and competition explain forest mortality patterns under extreme drought. *Ecol.*
- 614 Lett. 20, 78-86.
- 615
- 616

617 **Table 1:** Five best candidate models ([model #1-5](#)) of SDC, based on AIC comparison.
 618 Coefficients are relative to a model where [agency](#) = CDF (CAL FIRE), class = SUP
 619 (suppression), and region = SCSN (Southern Cascades/Sierra Nevada). [USFS](#) = US Forest
 620 Service, NPS = US National Park Service, WFU = Wildland Fire Use, max_tmmx = maximum
 621 daily high temperature during burn window, max_tmmn = maximum daily low temperature
 622 during burn window, NW = northwestern region of California, max_bi = maximum daily burn
 623 index during burn window, [and](#) min_rmax = minimum daily high humidity during burn window.

Model AIC /coefficients	Model #				
	1	2	3	4	5
AIC	901.721	902.151	902.154	902.724	902.818
(Intercept)	7.136	5.557	7.66	5.423	5.972
agencyNPS	0.478	0.506	0.475	0.472	0.504
agencyUSFS	0.196	0.214	0.174	0.189	0.194
classWFU	0.377	0.379	0.381	0.401	0.381
fire_year	-0.006	-0.005	-0.006	-0.005	-0.005
max_tmmx	-0.024	-0.012	-0.028	-0.023	-0.015
max_tmmn	0.019		0.019	0.019	
regionNW			0.09		0.083
max_bi				-0.002	
min_rmax					

624

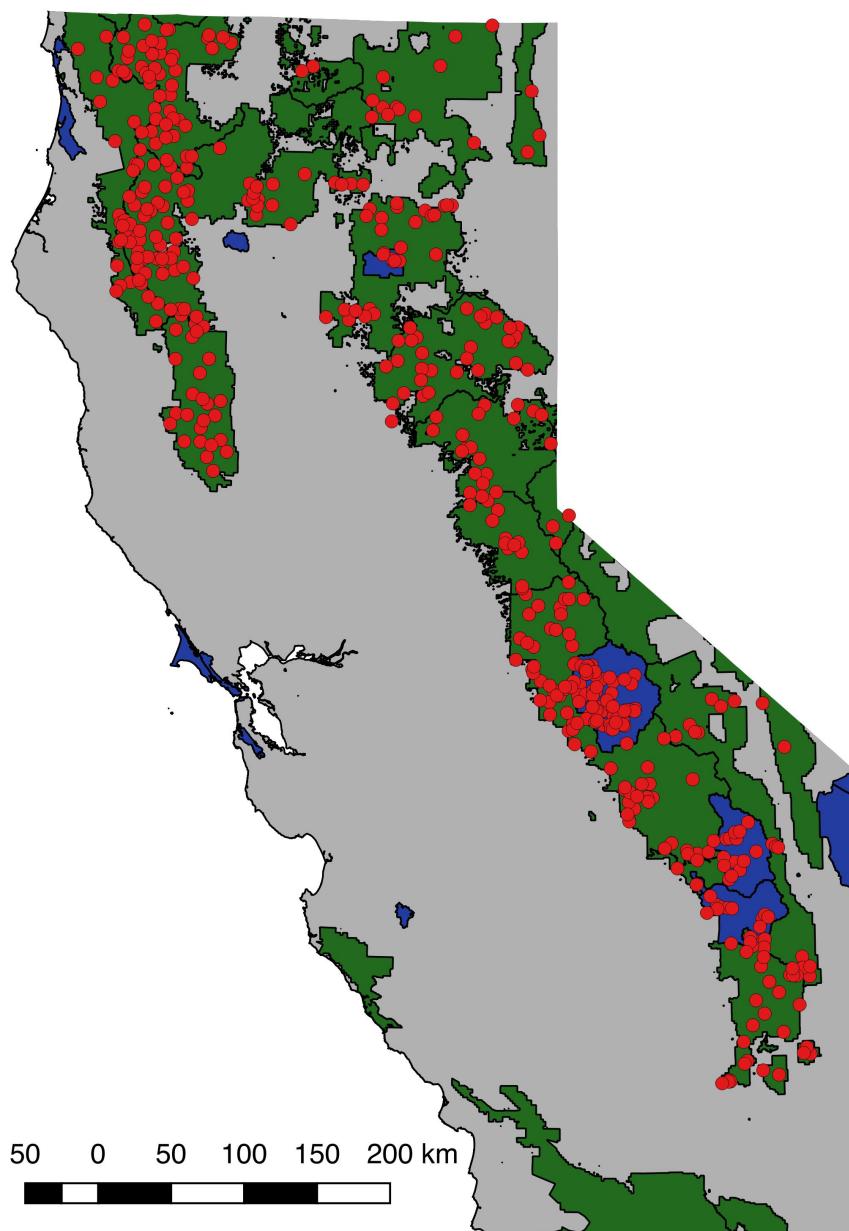
625

626 **Table 2:** Summary of fire statistics across agency and management class. Fires with agency =
 627 NA were other agencies not among the three principal fire management agencies and with too
 628 few fires to draw meaningful conclusions (e.g. Bureau of Indian Affairs). Agency codes: CDF =
 629 CAL FIRE, USFS = US Forest Service, NPS = US National Park Service. Class codes: SUP =
 630 suppression fires, WFU = Wildland Fire Use fires. Weather variables are the maximum or
 631 minimum daily value over the burn period for a given fire, averaged over all fires in the sample.

agency	class	N	min size (ha)	median size (ha)	max size (ha)	median fire year	mean maximum high temperature	mean maximum burn index	mean maximum low temperature	mean minimum high humidity
CDF	SUP	31	83	828.0	39265	2000	32.7	70.9	14.5	40.0
NPS	SUP	33	84	414.0	24123	1996	27.8	67.7	12.7	36.4
NPS	WFU	54	106	642.5	4143	1996	25.9	74.3	11.7	29.1
USFS	SUP	340	85	1381.5	104038	2003	32.5	69.1	15.4	37.5
USFS	WFU	17	140	928.0	2420	2003	24.9	79.3	10.4	28.2
NA	SUP	2	590	905.0	1220	2010	28.5	76.7	16.2	36.5

632

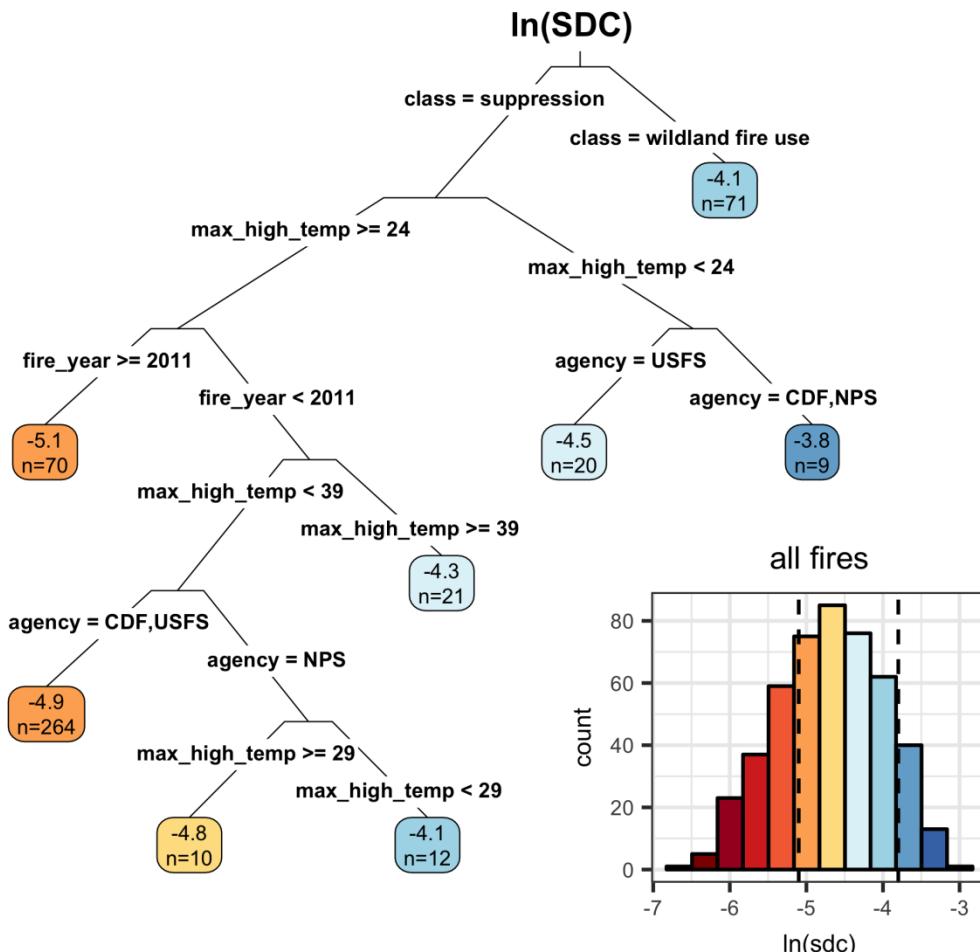
633 **Figure 1:** Locations of the 477 fires in this study (red points). All fires burned within California
634 (gray shading) with ~~here~~ at least 50% of the fire perimeters ~~burned~~ in mixed-conifer forest on
635 land managed by either the US Forest Service (USFS; green shading) or the US National Park
636 Service (NPS; blue shading), including fires managed by USFS, NPS, and CAL FIRE.
637 [1-column figure]



638

639 **Figure 12:** Regression tree based off-on model 2 (Table 1). Values in ovals are ln-transformed
 640 SDC values, indicating mean ln(SDC) values for fires in a given cluster, with sample size
 641 indicated. Variables are fire management class (suppression, Wildland Fire-Use), maximum
 642 daily high temperature during the burn window (max_high_temp), fire year (1984 through 2015),
 643 and fire management agency (National Park Service *NPS*, US Forest Service *USFS*, or CAL
 644 FIRE *CDF*). Inset figure displays the distribution of ln(SDC) across all 477 fires analyzed in this
 645 study, with dashed lines indicating the range of ln(SDC) values in the ovals. Colors of the ovals
 646 correspond to the histogram bins in the inset figure.

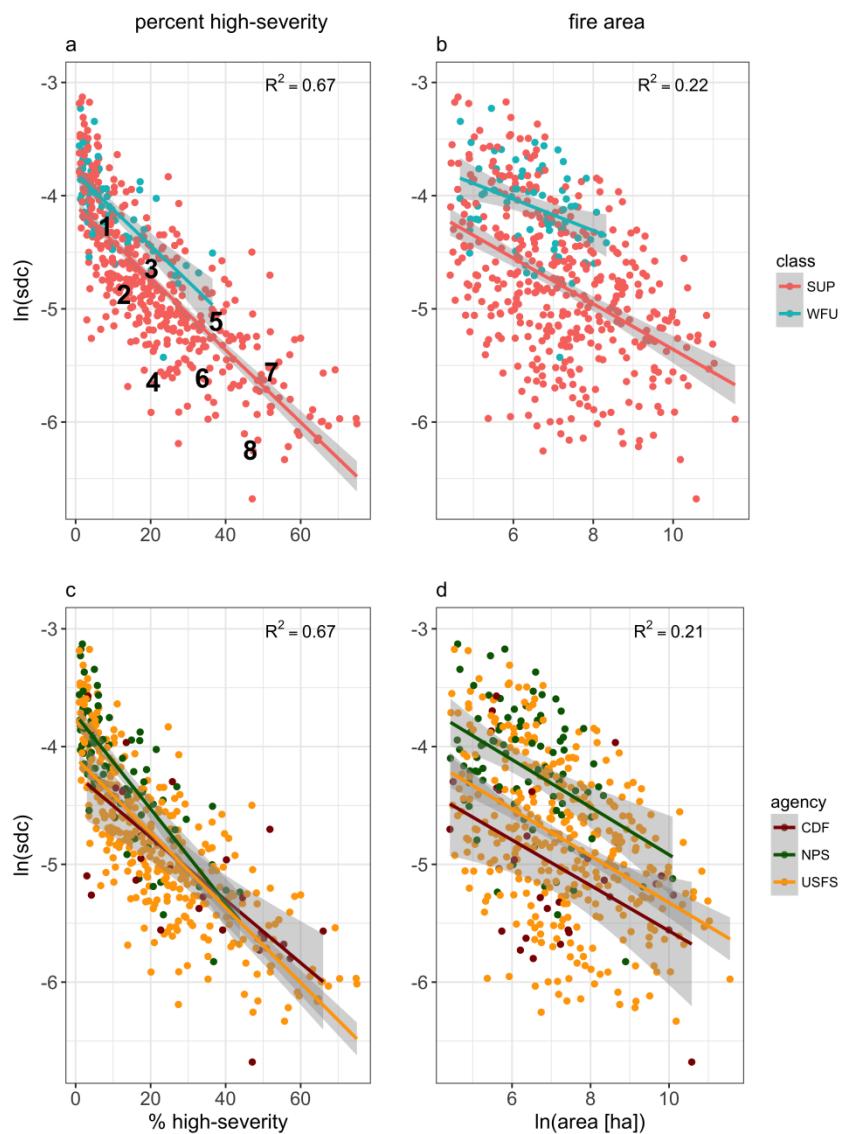
647 [2-column figure]



648

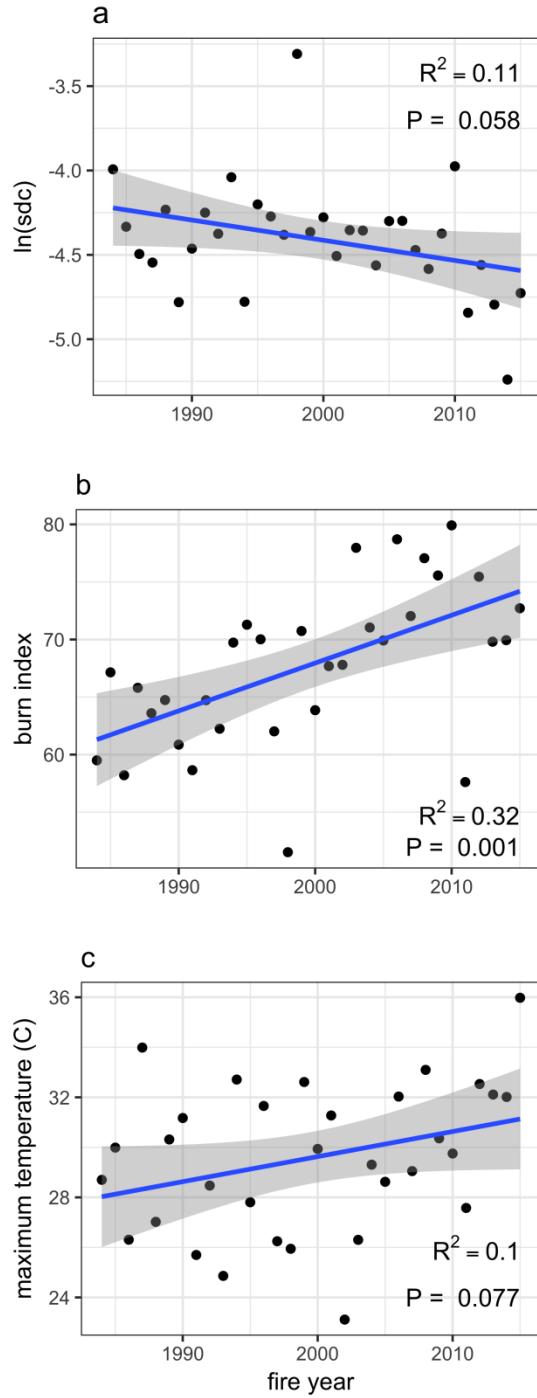
649

650 **Figure 23:** Relationship between $\ln(sdc)$ and percent high-severity (using a 90% basal area
 651 mortality threshold) and fire size (in ha). Fire class (suppression [SUP] vs Wildland Fire Use
 652 [WFU]) and managing agency (CAL FIRE [CDF], US National Park Service [NPS] and US
 653 Forest Service [USFS]) explain differences in $\ln(sdc)$ among fires with otherwise similar percent
 654 high-severity or similar fire size. Numbers in panel (a) correspond to fires used in Figure 65 to
 655 illustrate different stand-replacing patch configurations with similar percent high-severity. Test
 656 statistics for inter-group comparisons given in text.
 657 [1.5 column figure]



658

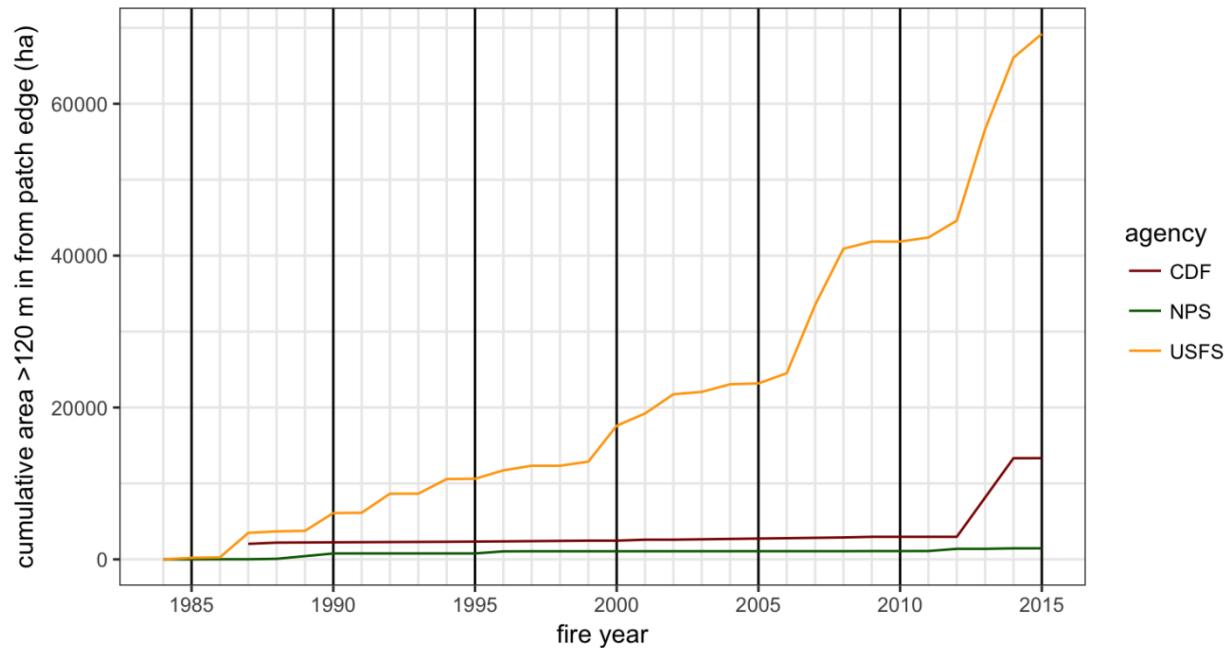
659 **Figure 34:** Trends over time in mean annual SDC mean annual(a), mean annual maximum burn
660 index during the burn window (eb), and mean annual maximum high temperature during the
661 burn window (ec). Panels (b, d, f) show 5-year moving averages of annual data from panels (a, c,
662 e) respectively.
663 [1 column figure]



664

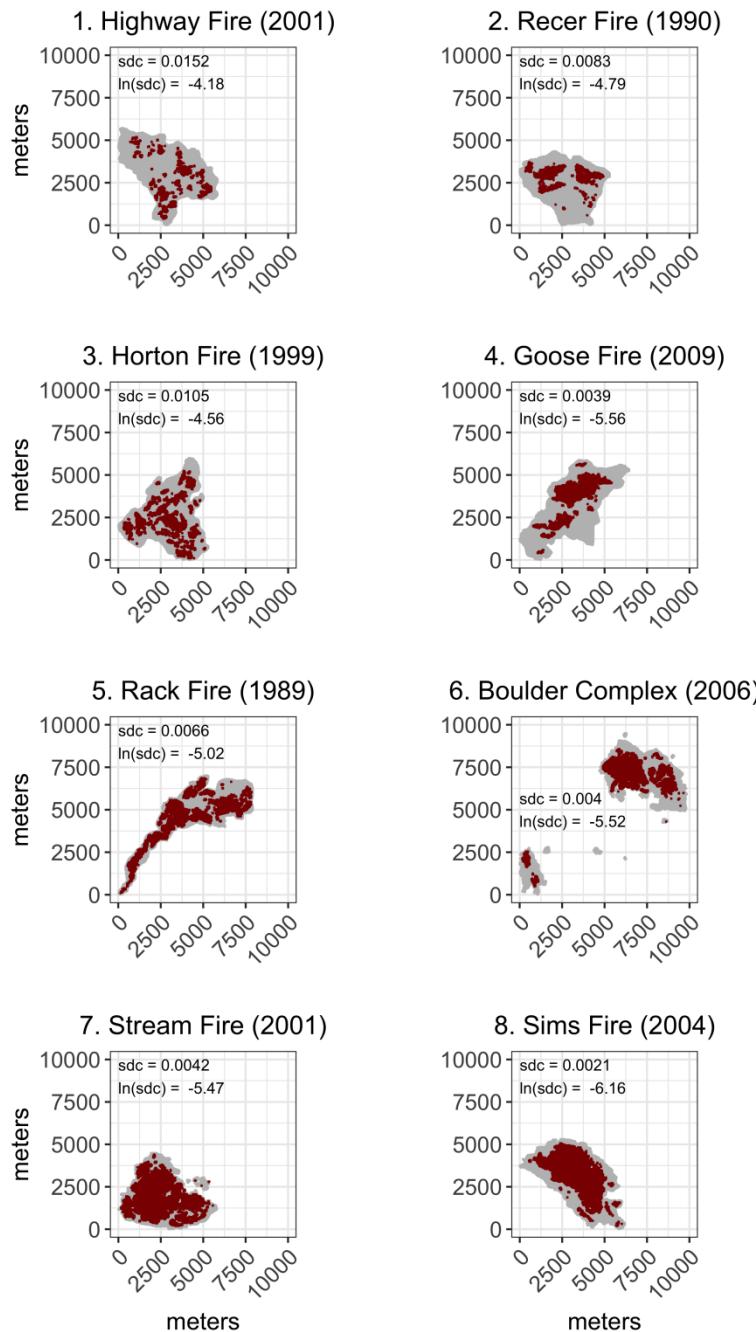
665 **Figure 45:** Increase in cumulative stand-replacing area greater than 120 m from edge since 1984,
666 by agency (CAL FIRE [CDF], US National Park Service [NPS] and US Forest Service [USFS]).
667 “0” represents the value in 1984, as no mapped fires were available before then. In 2015, the
668 cumulative area was 19760 ha for CDF (12.6% of total burned area for CDF), 3499 ha for NPS

669 (3.0% of total burned area for NPS), and 1669378 ha for USFS (7.8% of the total burned area for
670 USFS).



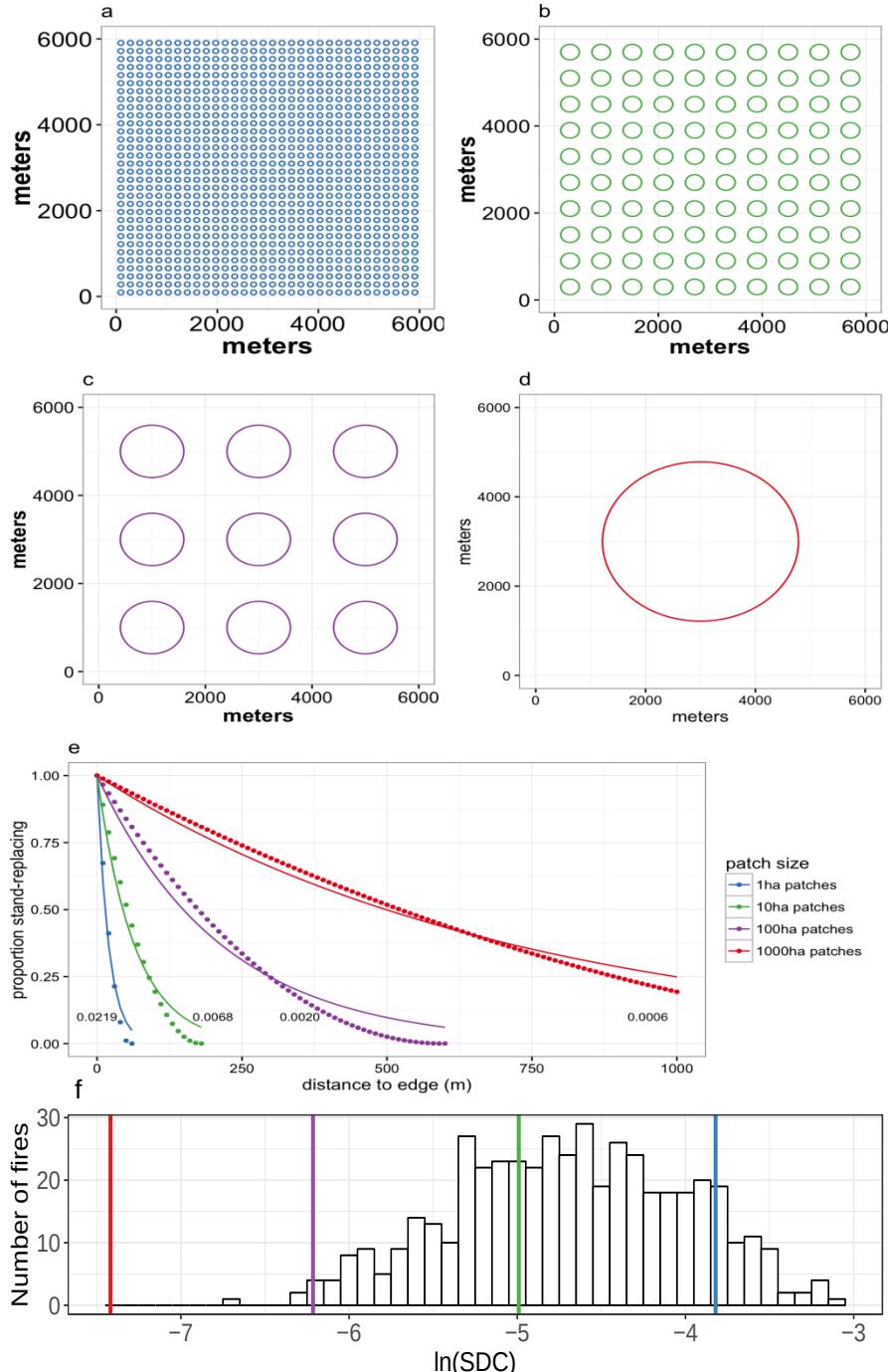
671
672
673
674
675
676
677
678
679
680
681
682
683

Figure 56: Examples of SDC for a range of fires. Fires in the same row have similar areas and percent high-severity, corresponding to numbers 1-8 in Figure 3. SDC values are shown on the figure. Fires in the right column have lower SDC values than comparably-sized fires in the left column.



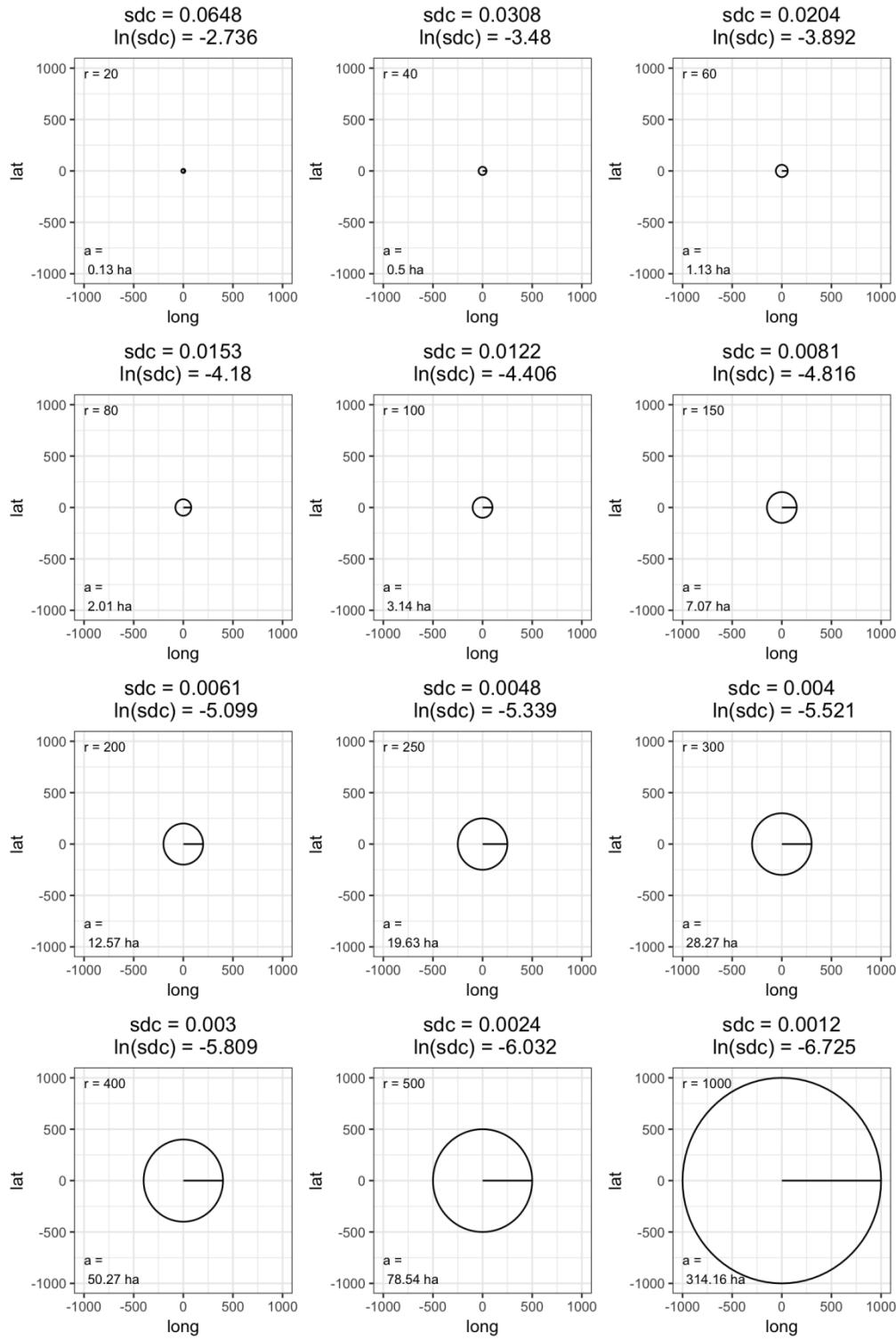
1 **Appendix 1: Supplementary Figures**

2 **Figure A1:** Example calculation of SDC curves (panel e) fit to four hypothetical fires, with 1000
3 ha of stand-replacing fire distributed in 1, 10, 1000 and 1000 ha patches (panels a-d).
4 Distribution of $\ln(\text{SDC})$ values shown in panel f, with colored lines matching panel e. Modified
5 from Collins et al. (2017).

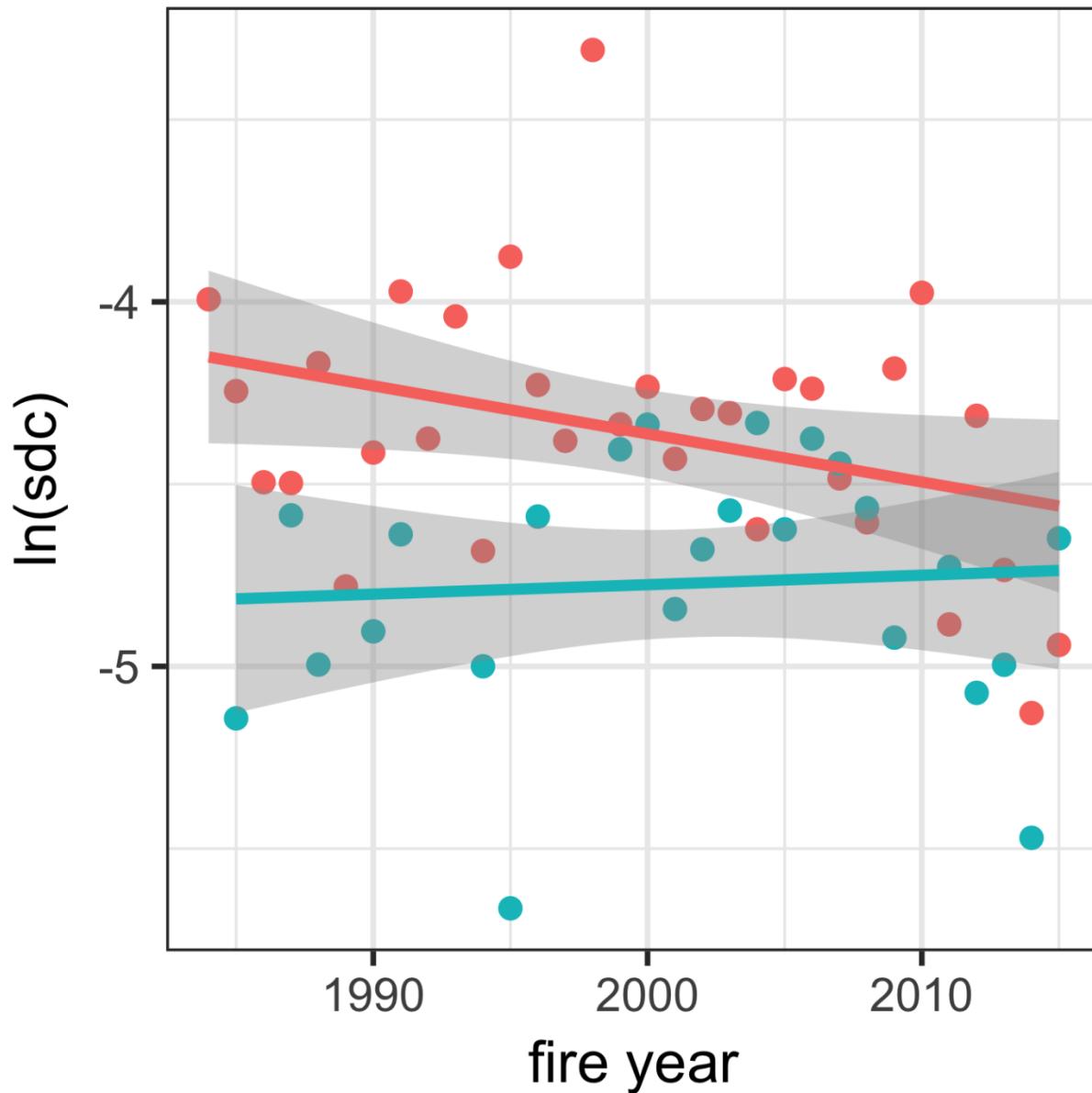


7

8 **Figure A2:** Range of possible SDC values as a function of average patch radius (radius given as
9 r in m, area given as a in ha).



12 **Figure A3:** Change in $\ln(\text{SDC})$ over time, distinguishing between the Southern Cascade/Sierra
13 Nevada (red) region and northwestern California (teal). The trend of decreasing mean annual
14 $\ln(\text{sdc})$ was significant in the SCSN ($R^2 = 0.12$, $t = 2.05$, $P = .049$) but not in NW ($R^2 = 0.004$, $t =$
15 0.32 , $P = .750$). Shaded bands represent 95% confidence interval around regression line.



16