# Supplemental Information

## Supplemental methods

### Remote sensing vegetation characteristics, including forest structural variability

Vegetation characteristics can be measured using remotely-sensed imagery (1–3) and texture analysis of this imagery can quantify ecologically relevant local environmental heterogeneity across broad spatial extents (4–8), which may be used as a direct measure of ecosystem resilience (9). Developed for image classification and computer vision, texture analysis characterizes each pixel in an image by a summary statistic of its neighboring pixels, and represents a measure of local heterogeneity which itself varies across the landscape (10). Texture analysis of forested areas detects heterogeneity of overstory vegetation, which corresponds to fuel loading and continuity, capturing the primary influence of vegetation structure on fire behavior.

### Remote sensing potential annual heat load

We used the digital elevation model to calculate the potential annual heat load (Supplemental Equation 5 at each pixel, which is an integrated measure of latitude, slope, and a folding transformation of aspect about the northeast-southwest line, such that northeast becomes 0 radians and southwest becomes radians (11, 12):

Where is the potential annual heat load, is a transformation of aspect in radians, and both and are extracted from a digital elevation model with units of radians.

### Remote sensing wildfire severity

Wildfire severity typically describes the proportion of vegetation mortality resulting from fire (13), and can be measured by comparing pre- and postfire satellite imagery for a specific area (14). This usually requires considerable manual effort for image collation and processing, followed by calibration with field data (15–23). Herculean efforts to measure severity across broad spatial extents, such as the Monitoring Trends in Burn Severity project (24), exist but often must sacrifice coverage of smaller fires which are far more common (25), may have different severity expectations compared to larger fires (26, 27), and are generally important contributors to global fire effects (28). Automated efforts to remotely assess wildfire have arisen, but they tend to focus on more aggregate measures of wildfire such as whether an area burned or the probability that it burned rather than the severity of the burn (29–32), but see (33, 34). Here, we present a method to automate the measurement of wildfire severity using minimal user inputs: a geometry of interest (a wildfire perimeter or a field plot location) and an alarm date (the date the fire was discovered). This information is readily available in many fire-prone areas (such as California, via the Fire and Resource Assessment Program; <http://frap.fire.ca.gov/projects/fire_data/fire_perimeters_index>) or could be derived using existing products (such as the Landsat Burned Area Essential Climate Variable product described in (32)).

We calibrate 28 configurations of our algorithmic approach to ground-based wildfire severity measurements, and select the best performing severity metric to generate a comprehensive, system-wide severity dataset. Our approach more than doubles the number of fire events represented from 430 to 972, though only increases the total burned area represented from 7.44e+05 to 7.69e+05 hectares because most of the additional fires are small.

#### Fetching and processing pre- and postfire imagery

For each fire perimeter, we fetched a time series of prefire Landsat images starting the day before the fire alarm date and extending backward in time by a pre-deined time window. An analogous postfire time series of Landsat imagery was fetched exactly one year after the date range used to filter the prefire collection. We tested 4 time windows, 16, 32, 48, or 64 days, which were chosen to ensure that at least 1, 2, 3, or 4 Landsat images were captured by the date range (Supplemental Fig. 1). The Landsat archive we filtered included imagery from Landsat 4, 5, 7, and 8, so each pre- and postfire image collection may contain a mix of scenes from different satellite sources to enhance coverage. For each image in the pre- and postfire image collections, we masked pixels that were not clear (i.e., clouds, cloud shadows, snow, and water) using the CFMask algorithm (35).

For each Landsat image in the prefire and postfire collections, we calculated standard indices that capture vegetation cover and fire effects such as charring. Normalized difference vegetation index (NDVI) correlates with vegetation density, canopy cover, and leaf area index (1). Normalized burn ratio (NBR) and normalized burn ratio version 2 (NBR2) respond strongly to fire effects on vegetation (14, 32, 36–38) (Equations in Supplemental Methods).

We composited each pre- and postfire image collection (including the pixel values representing NDVI, NBR, and NBR2) into a single pre- and postfire image using a median reducer, which calculated the median of the unmasked values on a per-pixel basis across the stack of images in each collection. Composite pre- and postfire images can be successfully used to measure wildfire severity instead of using raw, individual images (34).

#### Spectral indices of wildfire severity

Using the composited images, we calculated commonly used metrics of remotely-sensed wildfire severity to validate against ground-based data: the relative burn ratio (RBR) (20), the delta normalized burn ratio (dNBR) (15, 24), the relative delta normalized burn ratio (RdNBR) (15, 39), the delta normalized burn ratio 2 (dNBR2) (32), the relative delta normalized burn ratio 2 (RdNBR2), and the delta normalized difference vegetation index (dNDVI) (24). We also calculated an analogous metric to RdNBR using NDVI: the relative delta normalized difference vegetation index (RdNDVI). We calculated the delta severity indices (dNBR, dNBR2, dNDVI) without multiplying by a rescaling constant (e.g., we did not multiply the result by 1000 as in (15)). Following (33), we did not correct the delta indices using a phenological offset value, as our approach implicitly accounts for phenology by incorporating multiple cloud-free images across the same time window both before the fire and one year later.

Normalized difference vegetation index (NDVI; Supplemental Equation 1) correlates with vegetation density, canopy cover, and leaf area index (1). Normalized difference moisture index (NDMI; Supplemental Equation 2) correlates with similar vegetation characteristics as NDVI, but doesn’t saturate at high levels of foliar biomass (40). Normalized burn ratio (NBR; Supplemental Equation 3) and normalized burn ratio version 2 (NBR2; Supplemental Equation 4) respond strongly to fire effects on vegetation (14, 32, 36–38).

Where is the near infrared band (band 4 on Landsat 4, 5, and 7; band 5 on Landsat 8) and is the red band (band 3 on Landsat 4, 5, and 7; band 4 on Landsat 8), is the first short wave infrared band (band 5 on Landsat 4, 5, and 7; band 4 on Landsat 8), is the second short wave infrared band (band 7 on Landsat 4, 5, 7, and 8)

We calculated the delta severity indices (dNBR, dNBR2, dNDVI) by subtracting the respective postfire indices from the prefire indices (NBR, NBR2, and NDVI) without multiplying by a rescaling constant (e.g., we did not multiply the result by 1000 as in (15); Supplemental Equation 6). Following (33), we chose not to correct the delta indices using a phenological offset value (typically calculated as the delta index in homogeneous forest patch outside of the fire perimeter), as our approach implicitly accounts for phenology by incorporating multiple cloud-free images across the same time window both before the fire and one year later.

We calculated the relative delta severity indices, RdNBR and RdNDVI, by scaling the respective delta indices (dNBR and dNDVI) from Supplemental Equation 7 by a square root transformation of the absolute value of the prefire index:

We calculated the relative burn ratio (RBR) following (20) using Supplemental Equation 8:

#### Calibrating remotely-sensed wildfire severity with field-measured wildfire severity

We calibrated these 28 severity metrics with 208 field measures of fire effects to overstory vegetation— the overstory component of the Composite Burn Index (CBI)— from two previously published studies (42, 43). CBI is a metric of vegetation mortality across several vertical vegetation strata within a 30m diameter field plot, and the overstory component characterizes fire effects to the overstory vegetation specifically (14). CBI ranges from 0 (no fire impacts) to 3 (very high fire impacts), and has a long and successful history of use as a standard for calibrating remotely-sensed severity data in western U.S. dry forests (14–16, 18, 20, 21, 34).

Following (15), (16), (20), and (34), we fit a non-linear model to each remotely-sensed severity metric of the following form:

We fit the model in Supplemental Equation 9 for all 7 of our remotely-sensed severity metrics (RBR, dNBR, RdNBR, dNBR2, RdNBR2, dNDVI, RdNDVI) using 4 different time windows from which to collate satellite imagery (16, 32, 48, and 64 days). Following (18), (20), and (34), we used bilinear interpolation to extract remotely-sensed severity at the locations of the CBI field plots to better align remote and field measurements. We also extracted remotely-sensed severity values using bicubic interpolation, which produces smoother imagery but is more computationally demanding. In total, we fit 56 models (7 severity measures, 4 time windows, 2 interpolation methods) and performed five-fold cross validation using the modelr and purrr packages in R (44–46). To compare goodness of model fits with (15), (16), and (20), we report the average R2 value from the cross validation for each of the 56 models.

## Supplemental figures and tables

Supplemental Table 1: Comparison of models used to validate and calibrate remotely sensed wildfire severity with ground-based composite burn index (CBI) severity sorted in descending order by the R2 value from a 5-fold cross validation. A total of 56 models were tested representing all possible combinations of 7 different measures of wildfire severity (RBR, dNBR, dNBR2, RdNBR, RdNBR2, dNDVI, and RdNDVI), 4 different time windows in which Landsat imagery was acquired and summarized with a median reducer on a pixel-by-pixel basis (16 days, 32 days, 48 days, and 64 days), and two different interpolation methods (bilinear and bicubic). The three parameters (, , and ) from the nonlinear model fit described in Eq. 1 are reported. For each model, the value of the remotely sensed wildfire severity measurement corresponding to the lower bounds of 3 commonly used categories of severity are reported (‘low’ corresponds to a CBI value of 0.1, ‘mod’ corresponds to a CBI value of 1.25, and ‘high’ corresponds to a CBI value of 2.25)

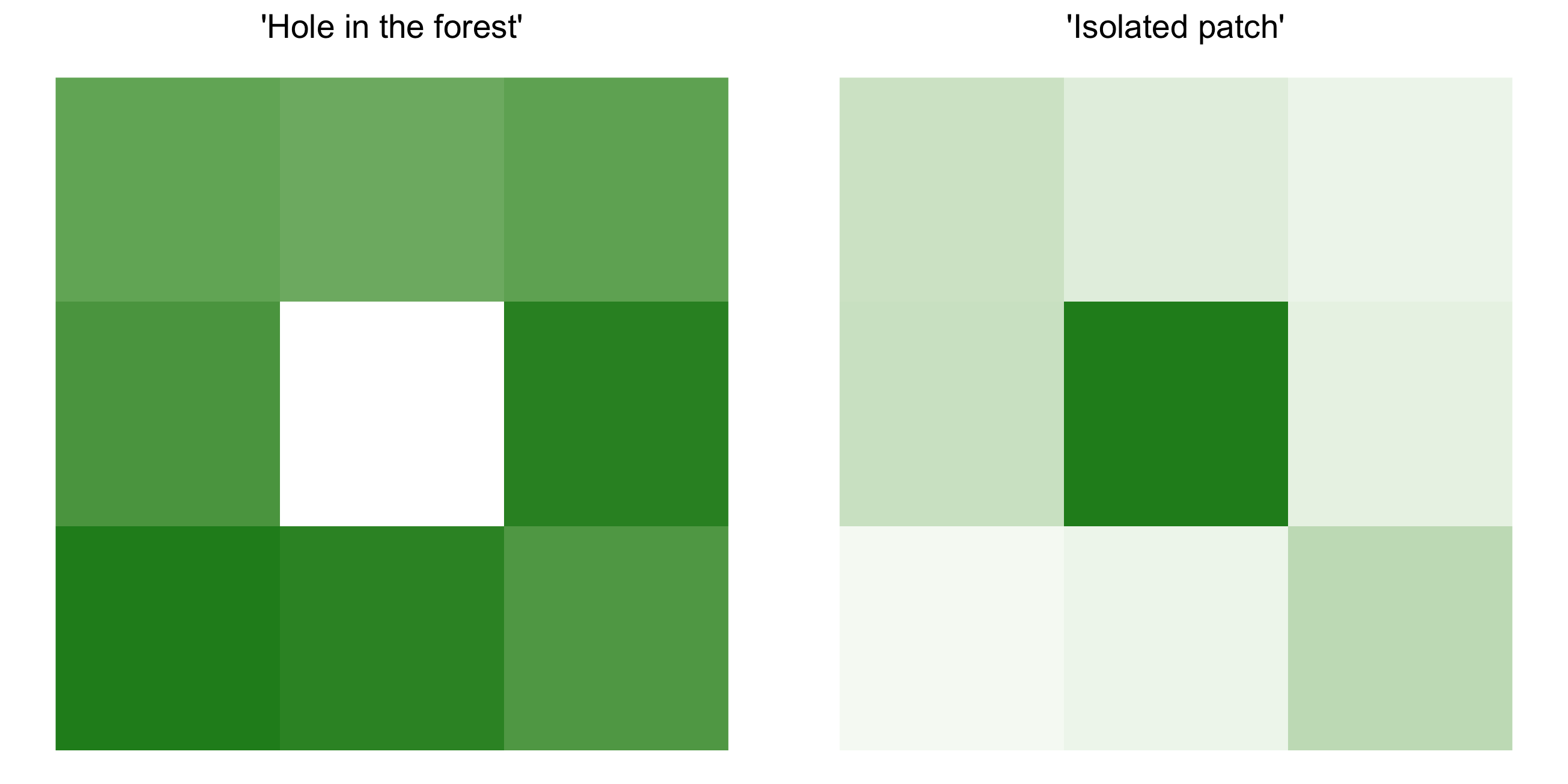
|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Rank | Severity measure | Time window | Interpolation | k-fold R2 |  |  |  | low | mod | high |
| 1 | RBR | 48 | bicubic | 0.82 | 0.014 | 0.028 | 1.001 | 0.045 | 0.113 | 0.282 |
| 2 | RdNBR | 32 | bilinear | 0.813 | -0.483 | 3.061 | 0.857 | 2.852 | 8.45 | 20.56 |
| 3 | RdNDVI | 48 | bilinear | 0.809 | -2.144 | 3.273 | 0.609 | 1.335 | 4.867 | 10.75 |
| 4 | RBR | 32 | bilinear | 0.807 | 0.014 | 0.029 | 0.985 | 0.046 | 0.113 | 0.28 |
| 5 | RdNDVI | 64 | bicubic | 0.805 | -2.524 | 3.57 | 0.59 | 1.263 | 4.936 | 10.93 |
| 6 | RBR | 64 | bicubic | 0.805 | 0.016 | 0.027 | 1.01 | 0.046 | 0.113 | 0.283 |
| 7 | RdNDVI | 32 | bicubic | 0.803 | -2.737 | 3.308 | 0.619 | 0.782 | 4.436 | 10.59 |
| 8 | RBR | 64 | bilinear | 0.802 | 0.017 | 0.027 | 1.003 | 0.047 | 0.113 | 0.279 |
| 9 | RdNDVI | 32 | bilinear | 0.801 | -2.531 | 3.176 | 0.624 | 0.849 | 4.393 | 10.39 |
| 10 | RdNDVI | 48 | bicubic | 0.797 | -2.623 | 3.624 | 0.587 | 1.22 | 4.922 | 10.94 |
| 11 | RdNDVI | 64 | bilinear | 0.796 | -2.14 | 3.287 | 0.607 | 1.353 | 4.876 | 10.73 |
| 12 | RdNBR | 64 | bilinear | 0.792 | -0.42 | 3.031 | 0.862 | 2.884 | 8.483 | 20.66 |
| 13 | RBR | 48 | bilinear | 0.791 | 0.017 | 0.027 | 1.006 | 0.047 | 0.112 | 0.277 |
| 14 | RBR | 32 | bicubic | 0.79 | 0.013 | 0.029 | 0.994 | 0.045 | 0.114 | 0.284 |
| 15 | RdNBR | 48 | bicubic | 0.785 | -0.858 | 3.219 | 0.852 | 2.647 | 8.476 | 21.02 |
| 16 | RBR | 16 | bilinear | 0.781 | 0.021 | 0.026 | 1.016 | 0.05 | 0.114 | 0.278 |
| 17 | RdNBR | 32 | bicubic | 0.776 | -0.954 | 3.34 | 0.841 | 2.679 | 8.602 | 21.2 |
| 18 | dNDVI | 32 | bicubic | 0.776 | -0.058 | 0.073 | 0.65 | 0.02 | 0.106 | 0.257 |
| 19 | dNBR | 48 | bicubic | 0.775 | 0.03 | 0.035 | 1.069 | 0.068 | 0.161 | 0.413 |
| 20 | RdNBR | 16 | bilinear | 0.774 | 0.279 | 2.518 | 0.909 | 3.037 | 8.119 | 19.73 |
| 21 | dNDVI | 32 | bilinear | 0.772 | -0.053 | 0.07 | 0.656 | 0.022 | 0.105 | 0.252 |
| 22 | dNDVI | 48 | bicubic | 0.772 | -0.055 | 0.081 | 0.613 | 0.031 | 0.119 | 0.267 |
| 23 | dNBR | 32 | bilinear | 0.77 | 0.029 | 0.036 | 1.048 | 0.069 | 0.163 | 0.41 |
| 24 | RdNBR2 | 64 | bicubic | 0.766 | 2.102 | 0.416 | 1.24 | 2.572 | 4.059 | 8.861 |
| 25 | dNBR | 32 | bicubic | 0.764 | 0.028 | 0.036 | 1.057 | 0.068 | 0.163 | 0.417 |
| 26 | dNDVI | 48 | bilinear | 0.762 | -0.044 | 0.073 | 0.637 | 0.034 | 0.118 | 0.262 |
| 27 | RBR | 16 | bicubic | 0.761 | 0.021 | 0.026 | 1.028 | 0.049 | 0.114 | 0.281 |
| 28 | dNBR | 16 | bilinear | 0.76 | 0.033 | 0.036 | 1.048 | 0.073 | 0.167 | 0.417 |
| 29 | RdNBR2 | 32 | bilinear | 0.759 | 1.435 | 0.625 | 1.1 | 2.132 | 3.906 | 8.861 |
| 30 | RdNBR | 16 | bicubic | 0.758 | 0.37 | 2.446 | 0.926 | 3.053 | 8.149 | 20 |
| 31 | RdNBR2 | 32 | bicubic | 0.754 | 1.426 | 0.601 | 1.125 | 2.098 | 3.876 | 8.975 |
| 32 | dNBR | 64 | bicubic | 0.753 | 0.033 | 0.033 | 1.086 | 0.07 | 0.161 | 0.413 |
| 33 | dNBR | 64 | bilinear | 0.751 | 0.035 | 0.033 | 1.08 | 0.071 | 0.161 | 0.406 |
| 34 | RdNBR2 | 48 | bicubic | 0.751 | 1.835 | 0.46 | 1.209 | 2.354 | 3.919 | 8.818 |
| 35 | dNBR | 48 | bilinear | 0.748 | 0.035 | 0.033 | 1.076 | 0.071 | 0.161 | 0.405 |
| 36 | RdNDVI | 16 | bilinear | 0.747 | -0.983 | 2.503 | 0.678 | 1.695 | 4.856 | 10.52 |
| 37 | dNDVI | 64 | bicubic | 0.746 | -0.055 | 0.082 | 0.609 | 0.032 | 0.12 | 0.266 |
| 38 | dNDVI | 64 | bilinear | 0.741 | -0.046 | 0.075 | 0.627 | 0.034 | 0.118 | 0.261 |
| 39 | RdNBR2 | 48 | bilinear | 0.737 | 1.802 | 0.497 | 1.174 | 2.361 | 3.956 | 8.766 |
| 40 | RdNBR | 64 | bicubic | 0.737 | -1.448 | 3.651 | 0.819 | 2.515 | 8.717 | 21.61 |
| 41 | RdNBR2 | 64 | bilinear | 0.735 | 2.027 | 0.451 | 1.204 | 2.536 | 4.06 | 8.801 |
| 42 | dNBR | 16 | bicubic | 0.729 | 0.032 | 0.036 | 1.058 | 0.072 | 0.168 | 0.423 |
| 43 | dNBR2 | 32 | bilinear | 0.727 | 0.026 | 0.009 | 1.149 | 0.035 | 0.062 | 0.14 |
| 44 | dNDVI | 16 | bicubic | 0.726 | -0.03 | 0.065 | 0.674 | 0.04 | 0.121 | 0.267 |
| 45 | RdNDVI | 16 | bicubic | 0.725 | -1.248 | 2.681 | 0.665 | 1.618 | 4.908 | 10.72 |
| 46 | dNBR2 | 32 | bicubic | 0.715 | 0.025 | 0.008 | 1.177 | 0.035 | 0.061 | 0.142 |
| 47 | dNBR2 | 64 | bilinear | 0.714 | 0.036 | 0.006 | 1.283 | 0.043 | 0.064 | 0.137 |
| 48 | dNDVI | 16 | bilinear | 0.707 | -0.023 | 0.06 | 0.689 | 0.042 | 0.12 | 0.261 |
| 49 | dNBR2 | 48 | bilinear | 0.686 | 0.033 | 0.006 | 1.248 | 0.04 | 0.063 | 0.137 |
| 50 | RdNBR2 | 16 | bilinear | 0.682 | 1.928 | 0.465 | 1.189 | 2.452 | 3.983 | 8.676 |
| 51 | dNBR2 | 16 | bilinear | 0.662 | 0.03 | 0.009 | 1.138 | 0.04 | 0.066 | 0.143 |
| 52 | RdNBR2 | 16 | bicubic | 0.654 | 1.871 | 0.467 | 1.198 | 2.398 | 3.96 | 8.792 |
| 53 | dNBR2 | 16 | bicubic | 0.635 | 0.029 | 0.009 | 1.156 | 0.039 | 0.066 | 0.145 |
| 54 | RdNBR | 48 | bilinear | 0.63 | -3.445 | 5.132 | 0.724 | 2.072 | 9.235 | 22.7 |
| 55 | dNBR2 | 48 | bicubic | 0 | 0.033 | 0.006 | 1.284 | 0.04 | 0.062 | 0.138 |
| 56 | dNBR2 | 64 | bicubic | 0 | 0.037 | 0.005 | 1.313 | 0.043 | 0.064 | 0.139 |

Supplemental Table 2: Model parameter estimates for different neighborhood sizes. Values represent the mean parameter estimates with 95% credible intervals in parentheses.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Coefficient | 90m x 90m neighborhood | 150m x 150m neighborhood | 210m x 210m neighborhood | 270m x 270m neighborhood |
|  | -2.415 (-2.588, -2.255) | -2.432 (-2.605, -2.271) | -2.447 (-2.619, -2.279) | -2.45 (-2.618, -2.288) |
|  | -0.208 (-0.247, -0.17) | -0.212 (-0.255, -0.17) | -0.203 (-0.248, -0.158) | -0.195 (-0.242, -0.148) |
|  | 1.044 (0.911, 1.174) | 1.13 (1.028, 1.229) | 1.141 (1.057, 1.222) | 1.132 (1.056, 1.209) |
|  | -0.569 (-0.71, -0.423) | -0.564 (-0.709, -0.419) | -0.561 (-0.697, -0.428) | -0.565 (-0.712, -0.422) |
|  | 0.239 (0.208, 0.271) | 0.238 (0.205, 0.269) | 0.239 (0.207, 0.269) | 0.24 (0.209, 0.272) |
|  | -0.01 (-0.042, 0.022) | -0.006 (-0.039, 0.027) | -0.002 (-0.037, 0.032) | -0.002 (-0.036, 0.033) |
|  | -0.14 (-0.278, 0.002) | -0.265 (-0.381, -0.148) | -0.293 (-0.392, -0.193) | -0.293 (-0.389, -0.198) |
|  | 0.125 (0.029, 0.218) | 0.06 (-0.013, 0.135) | 0.022 (-0.045, 0.09) | 0.009 (-0.054, 0.072) |
|  | -0.129 (-0.223, -0.034) | -0.078 (-0.151, -0.006) | -0.03 (-0.095, 0.035) | -0.006 (-0.068, 0.054) |
|  | -0.037 (-0.081, 0.006) | -0.035 (-0.078, 0.01) | -0.03 (-0.076, 0.014) | -0.023 (-0.07, 0.023) |
|  | -0.573 (-0.62, -0.526) | -0.564 (-0.612, -0.516) | -0.549 (-0.596, -0.502) | -0.537 (-0.587, -0.49) |

![Supplemental Figure 1: Schematic for how Landsat imagery was assembled in order to make comparisons between pre- and post-fire conditions. This schematic depicts a 64-day window of image collation prior to the fire which comprise the pre-fire image collection. A similar, 64-day window collection of imagery is assembled one year after the pre-fire image collection.](data:application/pdf;base64,)

Supplemental Figure 1: Schematic for how Landsat imagery was assembled in order to make comparisons between pre- and post-fire conditions. This schematic depicts a 64-day window of image collation prior to the fire which comprise the pre-fire image collection. A similar, 64-day window collection of imagery is assembled one year after the pre-fire image collection.



Supplemental Figure 2: Conceptual diagram of ‘decoupling’ that sometimes occurs between the central pixel NDVI and the neighborhood mean NDVI. In each of these scenarios, our model results suggest that the probability that the central pixel burns at high severity is higher than expected given the additive effect of the covariates. The left panel depicts the “hole in the forest” decoupling, which occurs more frequently, and the right panel depicts the “isolated patch” decoupling.

# References

1. Rouse W, Haas RH, Deering W, Schell JA (1973) *MONITORING THE VERNAL ADVANCEMENT AND RETROGRADATION (GREEN WAVE EFFECT) OF NATURAL VEGETATION* (Goddard Space Flight Center, Greenbelt, MD, USA).

2. Asner GP, et al. (2016) Progressive forest canopy water loss during the 20122015 California drought. *Proceedings of the National Academy of Sciences* 113(2):E249–E255.

3. Young DJN, et al. (2017) Long-term climate and competition explain forest mortality patterns under extreme drought. *Ecology Letters* 20(1):78–86.

4. Wood EM, Pidgeon AM, Radeloff VC, Keuler NS (2012) Image texture as a remotely sensed measure of vegetation structure. *Remote Sensing of Environment* 121:516–526.

5. Huang Q, Swatantran A, Dubayah R, Goetz SJ (2014) The Influence of Vegetation Height Heterogeneity on Forest and Woodland Bird Species Richness across the United States. *PLoS ONE* 9(8):e103236.

6. Stein A, Gerstner K, Kreft H (2014) Environmental heterogeneity as a universal driver of species richness across taxa, biomes and spatial scales. *Ecology Letters* 17(7):866–880.

7. Tuanmu M-N, Jetz W (2015) A global, remote sensing-based characterization of terrestrial habitat heterogeneity for biodiversity and ecosystem modelling: Global habitat heterogeneity. *Global Ecology and Biogeography* 24(11):1329–1339.

8. Graham LJ, Spake R, Gillings S, Watts K, Eigenbrod F (2019) Incorporating fine-scale environmental heterogeneity into broad-extent models. *Methods in Ecology and Evolution* 10(6):767–778.

9. Kéfi S, et al. (2014) Early Warning Signals of Ecological Transitions: Methods for Spatial Patterns. *PLoS ONE* 9(3):e92097.

10. Haralick RM, Shanmugam K, Dinstein I (1973) Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics* SMC-3(6):610–621.

11. McCune B, Keon D (2002) Equations for potential annual direct incident radiation and heat load. *Journal of Vegetation Science* 13(4):603–606.

12. McCune B (2007) Improved estimates of incident radiation and heat load using non- parametric regression against topographic variables. *Journal of Vegetation Science* 18(5):751–754.

13. Keeley JE (2009) Fire intensity, fire severity and burn severity: A brief review and suggested usage. *International Journal of Wildland Fire* 18(1):116.

14. Key CH, Benson NC (2006) Landscape Assessment (LA). 55.

15. Miller JD, Thode AE (2007) Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment* 109(1):66–80.

16. Miller JD, et al. (2009) Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA. *Remote Sensing of Environment* 113(3):645–656.

17. De Santis A, Asner GP, Vaughan PJ, Knapp DE (2010) Mapping burn severity and burning efficiency in California using simulation models and Landsat imagery. *Remote Sensing of Environment* 114(7):1535–1545.

18. Cansler CA, McKenzie D (2012) How Robust Are Burn Severity Indices When Applied in a New Region? Evaluation of Alternate Field-Based and Remote-Sensing Methods. *Remote Sensing* 4(2):456–483.

19. Veraverbeke S, Hook SJ (2013) Evaluating spectral indices and spectral mixture analysis for assessing fire severity, combustion completeness and carbon emissions. *International Journal of Wildland Fire* 22(5):707.

20. Parks S, Dillon G, Miller C (2014) A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. *Remote Sensing* 6(3):1827–1844.

21. Prichard SJ, Kennedy MC (2014) Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. *Ecological Applications* 24(3):571–590.

22. Edwards AC, Russell-Smith J, Maier SW (2018) A comparison and validation of satellite-derived fire severity mapping techniques in fire prone north Australian savannas: Extreme fires and tree stem mortality. *Remote Sensing of Environment* 206:287–299.

23. Fernández-García V, et al. (2018) Burn severity metrics in fire-prone pine ecosystems along a climatic gradient using Landsat imagery. *Remote Sensing of Environment* 206:205–217.

24. Eidenshink J, et al. (2007) A Project for Monitoring Trends in Burn Severity. *Fire Ecology* 3(1):3–21.

25. Calkin DE, Gebert KM, Jones JG, Neilson RP (2005) Forest Service Large Fire Area Burned and Suppression Expenditure Trends, 19702002. *j for* 103(4):179–183.

26. Cansler CA, McKenzie D (2014) Climate, fire size, and biophysical setting control fire severity and spatial pattern in the northern Cascade Range, USA. *Ecological Applications* 24(5):1037–1056.

27. Harvey BJ, Donato DC, Turner MG (2016) Drivers and trends in landscape patterns of stand-replacing fire in forests of the US Northern Rocky Mountains (1984-2010). *Landscape Ecology* 31(10):2367–2383.

28. Randerson JT, Chen Y, Werf GR van der, Rogers BM, Morton DC (2012) Global burned area and biomass burning emissions from small fires. *Journal of Geophysical Research: Biogeosciences* 117(G4). doi:[10.1029/2012JG002128](https://doi.org/10.1029/2012JG002128).

29. Bastarrika A, Chuvieco E, Martín MP (2011) Mapping burned areas from Landsat TM/ETM+ data with a two-phase algorithm: Balancing omission and commission errors. *Remote Sensing of Environment* 115(4):1003–1012.

30. Goodwin NR, Collett LJ (2014) Development of an automated method for mapping fire history captured in Landsat TM and ETM+ time series across Queensland, Australia. *Remote Sensing of Environment* 148:206–221.

31. Boschetti L, Roy DP, Justice CO, Humber ML (2015) MODISLandsat fusion for large area 30m burned area mapping. *Remote Sensing of Environment* 161:27–42.

32. Hawbaker TJ, et al. (2017) Mapping burned areas using dense time-series of Landsat data. *Remote Sensing of Environment* 198:504–522.

33. Reilly MJ, et al. (2017) Contemporary patterns of fire extent and severity in forests of the Pacific Northwest, USA (1985-2010). *Ecosphere* 8(3):e01695.

34. Parks SA, et al. (2018) High-severity fire: Evaluating its key drivers and mapping its probability across western US forests. *Environmental Research Letters* 13(4):044037.

35. Foga S, et al. (2017) Cloud detection algorithm comparison and validation for operational Landsat data products. *Remote Sensing of Environment* 194:379–390.

36. García ML, Caselles V (1991) Mapping burns and natural reforestation using thematic Mapper data. *Geocarto International* 6(1):31–37.

37. USGS (2017) Landsat 4-7 Surface Reflectance (LEDAPS) Product Guide. 41.

38. USGS (2017) Landsat 8 Surface Reflectance Code (LASRC) Product Guide. 40.

39. Miller JD, Safford H (2012) TRENDS IN WILDFIRE SEVERITY: 1984 TO2010 IN THE SIERRA NEVADA, MODOC PLATEAU, AND SOUTHERN CASCADES, CALIFORNIA, USA. *Fire Ecology* 8(3):41–57.

40. Gao B-c (1996) NDWIA normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58(3):257–266.

41. Huesca M, García M, Roth KL, Casas A, Ustin SL (2016) Canopy structural attributes derived from AVIRIS imaging spectroscopy data in a mixed broadleaf/conifer forest. *Remote Sensing of Environment* 182:208–226.

42. Zhu Z, Key C, Ohlen D, Benson N (2006) *Evaluate Sensitivities of Burn-Severity Mapping Algorithms for Different Ecosystems and Fire Histories in the United States*.

43. Sikkink PG, et al. (2013) Composite Burn Index (CBI) data and field photos collected for the FIRESEV project, western United States. doi:[10.2737/RDS-2013-0017](https://doi.org/10.2737/RDS-2013-0017).

44. Wickham H (2019) *Modelr: Modelling Functions that Work with the Pipe* Available at: <https://CRAN.R-project.org/package=modelr>.

45. Henry L, Wickham H (2019) *Purrr: Functional Programming Tools* Available at: <https://CRAN.R-project.org/package=purrr>.

46. R Core Team (2018) *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical Computing, Vienna, Austria) Available at: <https://www.R-project.org/>.