# Supplemental Information

## Supplemental methods

Wildfire severity typically describes the proportion of vegetation mortality resulting from fire (1), and can be measured by comparing pre- and postfire satellite imagery for a specific area (2). This usually requires considerable manual effort for image collation and processing, followed by calibration with field data (3–11). Hurculean efforts to measure severity across broad spatial extents, such as the Monitoring Trends in Burn Severity project (12), exist but often must sacrifice coverage of smaller fires which are far more common (13), may have different severity expectations compared to larger fires (14, 15), and are generally important contributors to global fire effects (16). 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 (17–20), but see (21, 22). 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 (20)).

Vegetation characteristics can be measured using remotely-sensed imagery (23–25) and texture analysis of this imagery can quantify ecologically relevant local environmental heterogeneity across broad spatial extents (26–30), which may be used as a direct measure of ecosystem resilience (31). 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 (32). 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.

We calibrate 56 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.

Normalized difference vegetation index (NDVI; Supplemental Equation 1) correlates with vegetation density, canopy cover, and leaf area index (23). 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 (33). Normalized burn ratio (NBR; Supplemental Equation 3) and normalized burn ratio version 2 (NBR2; Supplemental Equation 4) respond strongly to fire effects on vegetation (2, 20, 35–37).

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 (3); Supplemental Equation 5). Following (21), 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 6 by a square root transformation of the absolute value of the prefire index:

We calculated the relative burn ratio (RBR) following **???** using Supplemental Equation 7:

We used the digital elevation model to calculate the potential annual heat load (Supplemental Equation 8 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 (38, 39):

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.

## 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)

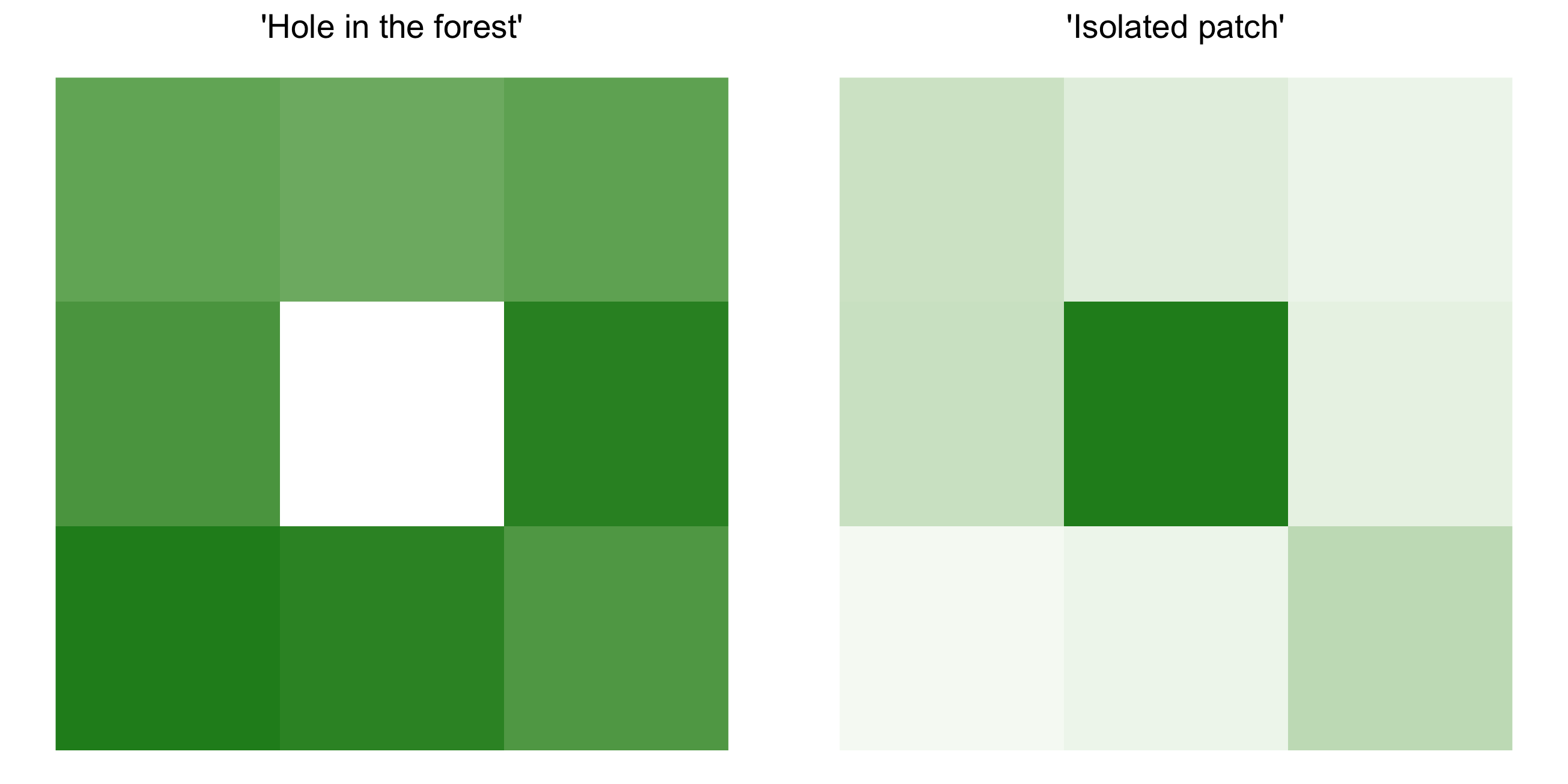
|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Rank | Severity measure | Time window | Interpolation | k-fold R2 |  |  |  | low | mod | high |
| 1 | RBR | 48 | bicubic | 0.82 | 0.014 | 0.028 | 1.001 | 0.045 | 0.113 | 0.282 |
| 2 | RdNBR | 32 | 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.

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