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Title

Beyond Average: A New Approach to Calculating Fire-Regime Departures Applied to Western United States Forests.

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Abstract

Background: Changes in climate and vegetation, in combination with fire exclusion, are altering and homogenizing fire regime attributes compared to historical conditions. Fire-regime changes are commonly quantified using departure metrics based on differences in measures of central tendency (i.e., means) between time periods. These metrics can mischaracterize complex changes to fire regime attributes because the distributions underlying these attributes are often not well described by parameters.

Results: We developed a non-parametric index of fire regime departure that quantifies distributional changes to fire regime attributes between time periods using the Earth Mover’s Distance. We used this departure metric to compare fire frequency and burn severity between historical (~1600-1880) and contemporary (1985-2021) time periods in western US forests. In addition, we compared the proposed metrics with a standard suite of measures of central tendency.

Departure metrics based on measures of central tendency reported lower relative departures within frequent fire forests and higher relative departures within infrequent fire forests than the EMD-based method. We found that 89% of western US forests are experiencing less frequent and more severe wildfires than historical baselines. Large departures are associated with increased human land-use intensity, and landscapes prioritized by the Wildfire Crisis Mitigation plan are on average, more departed than non-priority landscapes.

Conclusions: This proposed method captures facets of fire regime departures that metrics based on measures of central tendency cannot. These new metrics can aid the evaluation and targeting of treatments to restore historical fire regimes and manage the resilience of fire-prone landscapes.

Keywords: disturbance regimes; Earth Mover's Distance; fire modeling; fire regimes; historical fire regimes; management; wildfire; Wasserstein metric.

Resumen

Antecedentes: Cambios en el clima y la vegetación, en combinación con la exclusión histórica del fuego, están alterando y homogeneizando los atributos de los regímenes de fuegos, comparado con las condiciones históricas. Los cambios en los regímenes de fuegos son comúnmente cuantificados usando métricas basadas en las diferencias en las medidas de la tendencia central (i.e. la media) entre períodos de tiempo. Estas métricas pueden no caracterizar correctamente los cambios complejos en los atributos de los regímenes de fuegos, dado que las distribuciones que marcan esos atributos no siempre son bien descriptas por esos parámetros.

Resultados: Desarrollamos un índice no paramétrico de desviación del régimen de fuegos que cuantifica los cambios en los atributos de estos regímenes entre períodos de tiempo usando la "distancia debida al movimiento de la tierra" o *Earth Mover's Distance* (EMD) en idioma inglés. Usamos esta desviación para comparar la frecuencia histórica de fuego y la severidad de los mismos entre los períodos de tiempo (~1600-1880) y contemporáneo (1985-2021), en el oeste de los EEUU. Adicionalmente, comparamos las métricas propuestas con un conjunto estándar de medidas de tendencia central. Las desviaciones en esas métricas resultaron más pequeñas dentro del contexto de fuegos frecuentes y más grandes cuando fueron relacionadas a fuegos forestales infrecuentes que las obtenidas mediante el método EMD. Encontramos que el 89% de los incendios en los bosques del oeste de los EEUU están experimentando incendios menos frecuentes y más severos que lo que indican las bases históricas. Las grandes desviaciones están asociadas a un incremento humano en el uso de la tierra, y los paisajes priorizados en el plan de mitigación de la *Crisis de los Incendios* están asimismo más desviados que los paisajes no priorizados en este plan.

Conclusiones: El método propuesto en este trabajo captura facetas de desviaciones de los regímenes de incendios que las métricas usuales de la tendencia central no pueden capturar. Estas nuevas métricas pueden ayudar en la evaluación y apuntar a lograr objetivos que tengan como meta el restaurar los regímenes históricos de fuego y manejar la resiliencia en paisajes propensos al fuego.

Background

Contemporary fire regimes are increasingly departing from historical conditions (Haugo et al. 2019; Hagmann et al. 2021; McClure et al. 2024; Parks et al. 2025). Managing ecosystems under changing fire regimes requires an understanding of how fire attributes such as frequency and severity and their distribution are changing in space and time (Buma et al. 2019; Cochrane and Bowman 2021). In this paper, we developed a new fire regime departure method that accounts for changes in the distribution of fire frequency and severity (independently and combined) over space. We applied this new method to quantify departures over western US forests between simulated historical (~1600-1880) and measured contemporary (1985-2021) time periods across the western US.

Wildfire is a complex and critical ecosystem process that influences the composition, structure, and spatial patterns of forests in the western US and elsewhere (Balch et al. 2017; Sugihara et al. 2018; Coop et al. 2020). Lightning- and human-ignited wildfires have influenced western US forests for millennia, as evidenced by the numerous tree species with fire-adapted traits such as thick bark, resprouting, serotiny, and extensive paleoecological evidence (Whitlock et al. 2010; van Wagtendonk et al. 2018; Cochrane and Bowman 2021; Keeley and Pausas 2022). As a result, distinct forest types often have characteristic fire regime attributes that emerge from differences in local climate, topography, ignitions, and species' fire-adaptations. These attributes include frequency, severity (effects on the landscape, i.e., tree mortality), size, seasonality, and several others (van Wagtendonk et al. 2018; Cochrane and Bowman 2021). For example, cold forests dominated by lodgepole pine generally experience infrequent (>100-year return interval), large, stand-replacing fires during the summer and fall. Additionally, all fire regimes exhibit variability that drives landscape heterogeneity; in the case of cold forests, a proportion of fires may be small and burn at low severity, potentially leading to clearings and changes in species composition (Agee 1993; Cansler and McKenzie 2014; van Wagtendonk et al. 2018).

Fire regimes in the western US have changed since the late-1800s due to the removal of Indigenous burning, development, extensive livestock grazing, and persistent fire suppression (Cooper 1960; Eisenberg et al. 2019; Hessburg et al. 2021; Kreider et al. 2024). These actions and policies reduced fire frequency and annual area burned in western US forest ecosystems (Bowman et al. 2011; Swetnam et al. 2016; Roos et al. 2021; Kreider et al. 2024) and result in a contemporary (1985-2021) fire deficit (Marlon et al. 2012; McClure et al. 2024; Parks et al. 2025). Fire exclusion promotes accumulation of fuels beyond historical baselines in many ecosystems (Halofsky et al. 2020; Hagmann et al. 2021; Knight et al. 2022). When fires inevitably occur, they often burn at a relatively higher severity than was characteristic of historical fire regimes, particularly in forests characterized by low to moderate-severity fire (Mallek et al. 2013; Haugo et al. 2019; Williams et al. 2023; McClure et al. 2024). These recent changes in fire frequency and severity have modified other fire regime attributes, such as high severity patch size, which can drive changes to forest development (Cansler and McKenzie 2014; Jager et al. 2021; Cova et al. 2023; Davis et al. 2023; Buonanduci et al. 2023).

Understanding the extent to which contemporary fire regimes are departed from historical conditions (~1600-1880) is important for the management of forested landscapes (Keane et al. 2009; Keane et al. 2011; Whitlock et al. 2010). Historical baselines allow managers to place current fire regimes in context (Higgs et al. 2014) and to anticipate how altered fire regimes may result in novel post-fire forest trajectories (Higgs et al. 2014; Buma et al. 2019; Coop et al. 2020; Turner and Seidl 2023). Despite widespread acknowledgement that fire regime attributes are complex and better characterized by distributions (Pickett and White 1986; Agee 1993; van Wagtendonk et al. 2018), fire regime departure metrics generally rely on measures of central tendency (i.e., the mean). For example, mean fire return intervals (MFRI) and mean fire severities are often compared between time periods. Some methods account for variability in fire-attributes over time, for example, historical range of variation (HRV; Keane et al., 2009; Turner & Seidl, 2023). HRV describes the range of a chosen statistic (e.g., MFRI) over periods of time and compares that range to the contemporary period to assess departure (Keane et al. 2009; Whitlock et al. 2010; Haugo et al. 2019). However, departure methods that account for variability in space at fine resolutions (e.g. 30 m) across the western US are rare (e.g. Farris et al. 2010; Swetnam et al. 2011; Blankenship et al. 2015; Haugo et al. 2019), so investigators typically leverage expensive paleo-reconstructions to substitute time for space (Whitlock et al. 2010; Marlon et al. 2012; Buma et al. 2019; Higuera et al. 2021; Margolis et al. 2022).

Measures of central tendency inherently mask spatial variability in fire regimes. For example, MFRI, area burned, and mean fire severity collapse the spatial variance of fires into characteristic mean values on the landscape. Consider a hypothetical landscape that historically exhibited a broad range of fire frequencies, but contemporary fire exclusion has homogenized fire frequency (Fig. 1a). In this hypothetical landscape, the mean values for number of fire events are identical, yet the distribution of fire frequencies substantially differ between time periods (Fig. 1b). Similar patterns could be evident in terms of other fire-regime attributes over the hypothetical landscape. More broadly, departure metrics based on measures of central tendency do not quantify changes to the distribution of fire regime attributes and thus may obscure important changes in fire regime characteristics (Buma et al. 2019; Steel et al. 2021). Spatial variability in fire regimes contribute to ecosystem resilience and function by modifying forest structure. Thus, capturing this variability is crucial to forming a more complete understanding of fire regime departures (Martin and Sapsis 1992; Buma et al. 2019; Hessburg et al. 2021; Jager et al. 2021).

We propose using the Earth Mover's Distance (EMD; also known as the Wasserstein metric) to measure differences in the distribution of fire frequency and severity values between time periods. EMD is a non-parametric measure of distributional dissimilarity (Kantorovich and Rubinstein 1958; Vaserstein 1969; Dobrushin 1970) that can be conceptualized as the minimum effort needed to move blocks from one structure to another structure (Appendix A). It is similar to other distributional divergence measures such as the Kolmogorov-Smirnov test and Kullback-Leibler Divergence (Clement and Desch 2007). However, EMD is unique among these metrics because it preserves the units of the input distributions, can differentiate between distributions with complete separation, and is not affected by the ordering of the distributions (i.e. is a “true” distance metric, unlike Kullback-Leibler; Peyré and Cuturi 2019). Each EMD property allows for comparisons between distributions of fire regime attributes, which can vary widely in magnitude and shape. A comparison between distributional dissimilarity metrics and the equations for EMD are described in detail in Appendix A (Clement and Desch 2007; Panaretos and Zemel 2019; Cai and Lim 2022). The use of EMD is new in ecology, but it has shown promise in measuring a range of ecological variables such as climate model accuracy, ice deformation, among others (e.g. Hyun et al. 2022; Le et al. 2021; Parno et al. 2019; Vissio et al. 2020). Notably, Hoecker et al. (2023) calculated the EMD between contemporary and future fire attribute distributions within climate-defined fire regimes to project exposure to future fire regime changes. We aim to apply a similar approach by measuring EMD between historical and contemporary fire attribute distributions within geographically defined fire regimes to measure how fire regimes have changed from the past.

In this paper, we developed a new fire-regime departure method using EMD that accounts for changes in fire frequency and severity distributions over space. We applied this method to quantify departures over western US forests between simulated historical (~1600-1880) and measured contemporary (1985-2021) time periods across a standardized grid of the western US. Fire frequency and severity are particularly important fire regime attributes shaping forest ecosystems in western US forests. Frequency and severity correlate well with other fire attributes, and we have sufficient understanding to contiguously map both across the western US over both time periods (Swetnam et al. 2011; Yocom-Kent et al. 2015; LANDFIRE 2020; Cova et al. 2023; Buonaduci et al. 2023). Parallel to this new method, we calculated an existing suite of central tendency departure measures (Fire Regime Condition Class; S. Barrett et al. 2010) across the same landscapes to showcase how an EMD based metric captures distributional changes that metrics based on measures of central tendency would not. We quantified differences between the two types of metrics across the western US and developed two case studies to illustrate mechanisms behind the observed differences in departure metrics.

Our proposed EMD-based metric has the potential to provide ecologists, fire scientists, and land managers with a more nuanced understanding of fire regime departures in western US forests. Further, previous research indicates that human land uses influence fire regimes (Parks et al. 2014; Syphard et al. 2017; Hagmann et al. 2021; Kreider et al. 2024), so we investigated how our proposed metric of fire attribute departures relates to measures of human influence (e.g., percent of public vs private lands) across the western US. To understand the policy context of our approach, we applied our method across landscapes prioritized by the US "Wildfire Crisis Strategy" and discuss potential future uses in management (WCS; USFS 2022).

Methods

Overview

For forests in the western US, we characterized contemporary (1985-2021) fire regime distributions with continuous, satellite-derived fire severity data and fire perimeters from the Monitoring Trends in Burn Severity (Eidenshrink et al. 2007) program processed using the scripts from Parks et al. (2019). Historical distributions (37 simulated years approximating a random set of years between 1600 and 1880) were characterized using the LANDFIRE BioPhysical Setting product (BPS), which contains information regarding the average frequency of fires and proportion of those fires that burned under low, mixed, and high severity (LANDFIRE, 2020). Both the historical and contemporary datasets were 30-m resolution. To have consistent fire severity distributions between the two datasets, we calculated thresholds between the LANDFIRE fire severity classes and our chosen continuous measure of fire severity, the Composite Burn Index (CBI). Our full analysis used a 100-iteration bootstrap where we extracted fire frequency and severity of the contemporary period, then ran a simple probabilistic fire model to create distributions of fire frequency and fire severity in the historical period over the same pixels. Within each iteration, we calculated the EMD (equations in Appendix A) between these generated historical and contemporary distributions for fire frequency and fire severity, creating a distributional fire frequency departure (FFD), distributional fire severity departure (FSD), and a combined multivariate distributional fire regime departure index (MFRD; workflow for our main analysis shown in Fig. 2). The final outputs are the median values for each of our calculations across all bootstrap iterations, and they represent fire regime change within the given landscape. We applied our methods to multiple spatial containers across the western US for statistical analyses and for management use.

Study Area

We aggregated fire frequency and severity data at 30-m resolution pixels (0.09 ha) to multiple spatial containers including hexagonal grid cells (hexels; see Fig. 5 for study area), firesheds (Ager et al. 2021), designated wilderness areas, among other spatial containers (see data availability and supplement for details) across the western US. We chose standardized hexels to simply visualize our results and to enable continuous west-wide analyses without the artifacts from unequal distances associated with squares. LANDFIRE BPS maps pre-euro American settlement vegetation with expert and data derived fire regime simulation models developed over the mapped extent. BPS is focused on biophysical types over large, unequal, areal extents. Therefore we assume BPS FRI values represent the fire rotation period and chose a hexel size of 150,000 ha - the median mapped areal coverage among biophysical settings (LANDFIRE 2020). We did not measure hexels if they had greater than 50% overlap with the ocean, Canada, or Mexico. We also removed hexels if they contained less than 10% forested area, as fire regime departures are only calculated for forested pixels. Some hexels did not have contemporary wildfires, so we only calculated fire frequency departure within them. These frequency-only hexels are included in the data and displayed in Figure 5. For final analysis, we only measured hexels with complete frequency and severity departures, leaving 960 hexels covering 65 million ha of forest where 30.5 million ha burned during our contemporary study period (1985-2021) according to MTBS clipped to forested areas.

Main analysis

Frequency and severity distributions

For each hexel, we randomly sampled 0.1% of forested 30m pixels (mean sampled area = 674ha). We conducted sensitivity tests for other densities (and other parameters) in Appendix D, all of which show low sensitivity to sampling density. The primary benefit is that a low sampling density enables faster computations. Additionally, we replicated our main analysis 100 times to capture variation in simulations and to capture different samples within a hexel. We defined forest as those pixels labeled as “Conifer,” “Hardwood,” “Conifer-Hardwood,” or “Hardwood-Conifer” by LANDFIRE Existing Vegetation Type and BPS. We filtered to forested areas because satellite-derived Composite Burn Index (CBI) is not appropriate for use in non-forest systems (Parks et al. 2019). To produce contemporary fire frequency and severity distributions, we first processed the western US fire perimeters from Monitoring Trends in Burn Severity (MTBS) using the approach described by Parks et al. (2019) to obtain bias corrected CBI maps of every mapped fire greater than 404 hectares from 1985-2021. Parks et al., (2019) uses a Random Forest (Breiman 2001) model to predict CBI using multiple satellite derived spectral, climatic, and geographic variables in `Google Earth Engine` (Gorelick et al. 2017). These gridded CBI maps approximate field-based CBI measurements (Key and Benson 2006). Then we mosaicked individual fire maps into yearly fire maps from 1985-2021 and filtered to pixels (30m resolution) with >0.35 pre-fire NDVI as an additional step to remove pixels we presume to be non-forest (Parks et al. 2023).

We then counted the number of times each pixel burned (CBI values > 0) from 1985-2021 to produce the contemporary fire frequency distribution within each hexel. Similarly, we extracted fire severity estimates for each fire that occurred in each pixel, which were split into 16 evenly spaced bins with values ranging from 0-3.

To obtain historical fire frequency, we simulate the number of fires that occurred on each sampled pixel. That frequency is derived by the pixel’s MFRI given by BPS. We first extracted the mean fire return interval (MFRI) from the gridded biophysical setting layer at each sampled pixel. Then we randomly sampled from a binomial distribution at each pixel with parameters $n = 37$, $P = 1 / MFRI$, where n is the number of years (inclusive) in the contemporary period and P is the yearly probability of fire in the pixel given its biophysical setting. We then summarized these historical fire frequencies into a distribution of fire frequencies for each hexel.

The historical and contemporary datasets have different measures of fire severity. Fire severity from the historical dataset (BPS; LANDFIRE 2020) is a categorical estimate based on tree mortality thresholds (0-25% 25-75%, 75-100% canopy mortality for low, moderate, and high severity, respectively), while the contemporary dataset (Eidenshrink et al. 2007; Parks et al. 2019) uses continuous CBI, which assigns a 0-3 score based on aggregated, visual estimates of fire damage to herbs, shrubs, intermediate trees, large trees, and substrates one year following wildfire (Key and Benson 2006). We aligned these two datasets with ordered logistic regressions between CBI and fire severity classes defined by percent tree mortality.

To build regression models, we used the CBI plot data from Parks et al. (2023), with supporting percent canopy mortality measures. This includes 72 plots in the 2011 Miller Fire (Gila Wilderness in New Mexico) and 46 plots in the 2011 Hammer Creek fire (Bob Marshall Wilderness in Montana). First, we calculated plot level mortality using the weighted average of percent tree mortality by pre-fire tree coverage for intermediate and large trees. Then we modeled the relationship between CBI and percent tree mortality using two logistic regressions accounting for the ordering of severity classes (ordinal regression, e.g., mixed, and high severity are greater than low severity). We then computed the median and 95% confidence interval thresholds from a 1000 iteration bootstrap with thresholds optimized for greatest reliability using Cohen's kappa (Adjei and Karim, 2016; Manel et al., 2001; Yilmaz and Demirhan, 2023). Threshold values with 95% confidence intervals for low to mixed+high (T_{lm}) were 1.56[1.33, 1.72] and low+mixed to high (T_{mh}) were 2.01[1.92, 2.17] (Fig. 3, accuracy statistics in Appendix B). We used 95% bootstrapped confidence intervals to account for potential threshold uncertainty that may result from a small sample size (n=118 plots).

Because our mortality/CBI thresholds will directly affect the historical severity, and thus severity departures, we performed five sensitivity tests for different thresholds and their effects on our results (Appendix D) and visually compared thresholds to the results in a similar percent mortality by CBI dataset (Saberi et al. 2022). Four sensitivity tests set static thresholds at the extremes of our estimated thresholds using the lower and upper 95% confidence intervals. The fifth test used previously established thresholds from Miller and Thode (2007). We found that alternate thresholds did not significantly change results. Moreover, our thresholds closely match those reported by Saberi et al. (2022), who analyzed 315 plots across 14 fires in the Pacific Northwest. Saberi et al. found CBI values of approximately 1.3 at 25% tree mortality and ~2.0 at 75% mortality; our 95% confidence intervals were 1.33–1.72 and 1.92–2.17, respectively. However, they found CBI overestimated tree mortality in forests with large, open canopies (e.g., old-growth ponderosa pine), suggesting that landscapes dominated by these types may show inflated severity departures.

With the CBI/mortality class thresholds calculated above, we estimated historical fire severity for each historical wildfire estimated above. Essentially, we ask “if the estimated fire had occurred, what severity would it be?” For each estimated historical fire, we assigned a severity class of low, mixed, or high, via weighted random selection with weights given by the percent likelihood of each severity class as described by the biophysical setting. For each estimated severity, we then drew randomly from a uniform distribution within the bounds of CBI and the outer thresholds between severity classes determined above. For example, if we assigned a low severity fire, we drew from a uniform distribution with a lower bound of zero and an upper bound of 1.72, the upper confidence bound determined from our threshold calculation. A mixed classification would range from 1.33 to 2.17. In total, this fire severity simulation provides fire severity estimates for each fire in each sampled pixel based on the biophysical setting. With these estimated fire severities, we then created fire severity distributions using the same 16 bins as described for contemporary fires for each hexel.

Fire-regime Departure

To compare departures from historical fire regimes across hexels with different characteristic fire regimes, we rescaled our distributions by the historical mean and standard deviation, producing Z-scores. Then we computed the Earth Mover’s Distance on frequency and severity, from historical to contemporary, independently. Because we applied EMD to Z-scored distributions, we can interpret departures approximately as Z-scores relative to the mean of the historical fire regime. However, because the metric is distributional and fire frequency and severity are non-normal, we cannot make strong probabilistic inferences about what a given departure value represents, so we suggest using relative comparisons with Z-scores as a reference point (Panaretos and Zemel 2019). We recommend performing regionally specific investigations to interpret our departure values. To aid interpretation, the full datasets (see data availability) contain non-standardized departures to provide values in the original units, number of fires and CBI.

EMD can only be positive, so we modified attribute departures to show the net direction of change. We simply added a sign to the calculated fire frequency and severity departures based on the change in MFRI and percent burned at high severity. Signed distributional fire frequency (FFD) and signed distributional fire severity departures (FSD) are the resulting metrics. Positive values stand for a net reduction in fire frequency, and a net greater proportion of high severity fire in the contemporary period compared to historical, respectively.

Lastly, we calculated multivariate distributional fire regime departure index (MFRD), which represents the combined, additive effects of frequency and severity departures. FFD and FSD are normalized and continuous, so we combined them with the Euclidean distance $\sqrt{\mathrm{FFD}^2 + \mathrm{FSD}^2}$. Because we simulate fire regime attributes using 100 replicates, the key outputs for each hexel are the median normalized departures for FFD, FSD, and MFRD. See our data availability statement for pointers to our calculated statistics, descriptions of each, and locations for this analysis's results. State-wide differences (excluding extremes) in fire-regime departures were computed on MFRD across all hexels using 1-way ANOVA and pairwise linear contrasts on 20% trimmed means (Wilcox et al. 2000; Ozdemir et al. 2018; Wilcox 2022). All effect sizes use explanatory power (ξ) from Wilcox and Tian (2011), where small, medium, and large effect sizes correspond to 0.15, 0.35, and 0.50, respectively.

Comparison to mean statistics

We compared the proposed metrics to a commonly used suite of departure metrics based on means – the Fire-Regime Condition Class (FRCC; Barrett et al., 2010). In each hexel, we used the fire frequency and severity information generated above to calculate historical and contemporary MFRI and proportion burned at high severity (Barrett et al. 2010; Johnson and Gutsell 1994). These values were then used to calculate FRCC fire frequency departure (FFD_{cc}), fire severity departure (FSD_{cc}) and fire regime departure (FRD_{cc}) following the formulas in Barrett et al., (2010).

To assess the difference between the proposed EMD-based metrics and mean-based FRCC metrics, we first computed the absolute values of FFD and FSD. Next, we transformed these absolute values, along with MFRD and the FRCC departure statistics, into percentiles (denoted by a *P* subscript) among the western US hexels, placing them all on the same 0-100 scale where 100 is the most departed landscape for a given metric. We then subtracted the relevant FRCC departure from the relevant distributional departure (e.g., $\mathrm{MFRD}_P - \mathrm{FRD}_{cc.P}$

= Δ_P) to assess the difference in percentile between EMD-based metrics and FRCC. This process was performed on all datasets (Supplemental 3).

To demonstrate how FFD, FSD, and MFRD differ from FRCC and to unpack potential mechanisms behind these differences, we provide two granular case studies focused on the Kalmiopsis wilderness and Olympic National Park. These were chosen to clearly show two archetypes for differing FRCC and distributional departures. Specifically, we discuss the historical and contemporary MFRI, FFD_P, $FFD_{cc.P}$ and the underlying fire frequency distributions in both case studies.

Contemporary human influence and Management Prioritization

To investigate potential land-use and management associations to our proposed metrics, we first grouped hexels by state in the western US to analyze state-wide patterns of fire regime departure. Next, we analyzed relationships between MFRD and human influence. For each hexel, we calculated the average human footprint (Venter et al. 2016), the proportion covered by public lands, and the proportion covered by Wilderness and National Park lands (U.S. Geological Survey 2022). Human footprint combines eight human pressures (e.g., structures, roads, agriculture) into one characteristic score of human influence on landscapes (Venter et al. 2016). Human footprint, proportion of public lands, and proportion covered by Wilderness and National Park serve as indirect measures of fire exclusion activities and changes to the timing and frequency of anthropogenic ignitions (Balch et al. 2017; Boerigter et al. 2024). Each measure of human influence was grouped into five evenly spaced bins to address moderate skew and zero-inflation. We then calculated pairwise comparisons on 20% trimmed means (Wilcox 2022) to assess effect sizes of fire regime departure between different levels of human influence.

MFRD may associate with current federal fire management programs, which can indicate a pathway towards achieving agency goals, so we examined whether firesheds designated as priority landscapes are more departed than non-priority landscapes (US Forest Service, 2023). The fireshed dataset delimits landscapes with similar wildfire risks, land tenure, and planned management (Ager et al. 2021). Priority landscapes are designated by the US federal government as the firesheds (Ager et al. 2021) with highest need for future fire risk mitigation and the ability of communities to enact fire mitigation strategies (US Forest Service, 2023). For this analysis, we analyzed firesheds and then grouped them into priority and non-priority firesheds, determined by those with greater than 50% priority landscape coverage. We then calculated a t-test on 20% trimmed means (Wilcox 2022) between priority and non-priority firesheds to assess whether there are significant differences between these groups (Wilcox 2022).

Package Credits

Spatial data was manipulated using the `R` packages `sf` and `terra` (Hijmans et al. 2022; Pebesma 2018; R Core Team 2022). Tabular data was manipulated using `tidyverse`, `data.table` (Barrett et al. 2023; Wickham et al. 2019), and overall analysis was performed with `foreach, doParallel`, and `units` (Daniel et al. 2022b, a; Pebesma et al. 2023). Robust statistical tests were performed with `WSR2` (Mair et al., 2024). Figures were generated with `Rcolorbrewer`, `ggplot2` (Wickham et al. 2019; Neuwirth 2022) and in the `Julia` language with the packages `OptimalTransport`, `Makie`, and `Distributions` (Bezanson et al. 2017; Danisch and Krumbiegel 2021; Zhang et al. 2022; Lin et al. 2023). Calculation of EMD used the `transport` package in R (Schuhmacher et al. 2023).

Results

Fire Frequency and Severity Departures

Overwhelmingly (89% of 960 hexels), forested landscapes across the western US are burning less frequently and more severely today than in the historical period (Fig. 4). Fire regime departures were most prevalent in California and southern Oregon, however all states showed notable departures (Fig. 4, 5A). Although there are hexels in the other quadrants of Figure 4, they do not appear to have strong regional clustering (Fig. 5A). Of hexels that did not burn in the contemporary period (e.g., places with long FRIs or severe fire deficits), 32% had a frequency departure greater than 1 - near the 75th percentile frequency departure across all hexels.

Fire-Regime Departure metric

A map of the distributional, multivariate fire regime departure metric (MFRD; Fig. 5B) shows similar patterns as those described by distributional fire attribute departures. The 20% trimmed mean MFRD in California is statistically more departed than other states ($P < 0.001$, smallest California ξ: 0.68). Full pairwise comparisons among states can be found in Appendix C. California, Oregon, and Nevada are the three most departed western States while Colorado is the least departed, followed by Utah, and Idaho.

Relationship between Departure and Human Influence

We found that fire regime departures increased with land use intensity (as measured by the human footprint; Fig. 5C). Furthermore, fire regime departures decreased as the percent coverage of public lands and the percent coverage of wilderness and national park increased (Fig. 5C; pair-wise comparisons in Appendix C).

We found that priority landscapes are generally burning less frequently and more severely (Fig. 6). Additionally, priority landscapes have larger fire regime departures than non-priority landscapes (P value ≤ 0.001, $\xi = 0.33$).

Comparison to Fire-Regime Condition Class (FRCC)

We found that the difference in percentiles (Δ_P) for fire frequency departures between FRCC (FFD_{cc}) and the proposed EMD-based metrics (FFD) are higher in frequent fire forests of California, Arizona, and New Mexico, meaning distributional fire frequency departure is reporting relatively larger departures in those regions than FRCC. We also found negative changes in infrequent fire forests of western Washington, Nevada, and the Central Rocky Mountains, meaning that FRCC suggests larger fire regime departures than the distributional fire frequency metric (Fig. 7). The mean $\Delta_{P.\mathrm{frequency}}$, was -2 (SD = 39, IQR = [-23,25]). For fire severity (Fig. 7), we found that the region near Yellowstone National Park has high $\Delta_{P.\mathrm{severity}}$ and there are large negative values near the Colorado Plateau and Eastern Cascades. Mean $\Delta_{P.\mathrm{severity}}$ was 0 (SD = 31, IQR = [-21,16]). For MFRD (Fig. 7), we see the combined effects of both frequency and severity differences, and they show large positive differences in the Yellowstone region and large negative differences in the Colorado Plateau. The mean $\Delta_{P.\mathrm{regime}}$ was -1 (SD = 29, IQR = [-18,17]).

Discussion

Case study 1: Kalmiopsis Wilderness

The Kalmiopsis Wilderness Area typifies a general finding of our study; a historically frequent, small-fire ecosystem where a fire attribute (frequency in this case) homogenized due to a few, large fires, and where mean statistics likely underestimate the nature and extent of departure. We estimated a historical MFRI of 13 years, and the contemporary MFRI is 19 years. These values suggest a high frequency fire regime that changed minimally from 17th-19th century conditions (Fig. 8A). FRCC mean statistics reflect this with a 14th percentile departure in FFD_{cc}. Upon closer inspection of the fire frequency distributions (Fig. 8B), the contemporary distribution is more homogenous than our estimate of the historical distribution. FFD captures homogenization of the fire frequency distribution resulting in a 43rd percentile fire frequency departure, substantially higher than differences in MFRI as the FRCC departure suggests.

The proposed methods captured an ecological story about Kalmiopsis that MFRI could not tell but is supported by more intensive research methods. Paleoecological research suggests the historical fire regime of Kalmiopsis was maintained by cultural burning, resulting in a frequent fire ecosystem (MFRI 5-15yrs; Skinner et al. 2018; Knight et al. 2022). The loss of cultural burning has since led to the highest forest biomass in the last 3,000 years, indicating a lack of small, frequent fires that historically constrained biomass. In short, researchers used long-term fire scar records, oral histories, and biomass modeling to explain the homogenization of the landscape. Our analysis found a similar story despite using less intensive methods.

Case study 2: Olympic National Park

Conversely, Olympic National Park shows how mean statistics can artificially inflate departures. We estimated a historical MFRI of 308 years, a contemporary MFRI of ~16,000 years, and a corresponding FRCC fire frequency departure (FFD_{cc}) in the 90th percentile of western US wilderness areas and National Parks (Fig. 8A). FRCC departure is high because, as mean fire frequency approaches zero, common for infrequent fire ecosystems, the MFRI approaches infinity — inflating the mean departure statistic (Fig. 8C). Inflated departure statistics could lead to suboptimal resource allocation if they are used to guide management prioritization (Haugo et al. 2019; Donato et al. 2023). The proposed approach mitigates this issue, with a lower relative departure that is the 14th percentile. Again, prior research has shown similar, but they did so by using multiple lines of evidence that are difficult to combine into intuitive statistics (Gavin et al. 2013; Haugo et al. 2019).

The value of measuring changes in distributions

This distributional approach addresses at least two key limitations of measures of central tendency that can lead to overgeneralizations (Fig. 8). First, complex interactions between climate, land management, and vegetation may not change MFRI, but may change how fires burn in terms of their severity, such as the Kalmiopsis Wilderness case. Second, MFRI intrinsically approaches infinity when fire frequency is low, as shown in the Olympic National Park. Extending this logic across the western US (Fig. 7; Hagmann et al. 2021; Cova et al. 2023; Donato et al. 2023) we can infer large regions where means may mischaracterize fire regimes that changed in complex ways. For example, most of California has high differences in relative departure (Δ_P), like Kalmiopsis. It's likely that these landscapes are experiencing consolidation of area burned into individual, large fires rather than many small fires (Hagmann et al. 2021; Williams et al. 2023; Cova et al. 2023). These complex changes drive ecosystem development, and our proposed methods introduce an intuitive metric that accounts for some of this complexity (Coop et al. 2020; Jones and Tingley 2022; Davis et al. 2023).

Approaches like the one we have presented here, which use metrics that characterize the center, spread, and shape of statistical distributions and provide more nuanced information to natural resource managers than differences in means. Means (e.g., MFRI), and differences in means, may be more easily understood, but they can mischaracterize fire regime departures in areas with high spatial and temporal variance in wildfires (Fig 7 and 8). Management plans designed around mean values can sacrifice accuracy in favor of simplicity (Koontz et al. 2020; Stephens et al. 2020). Concepts like "historical range of variability," are also based on an understanding that shape and spread are relevant attributes of distributions that can inform management. These concepts have been operationalized by resources managers, for example, managers at Yosemite and Lassen Volcano National Parks use coarse distributions of acceptable fuel characteristics to design treatment implementation plans (Yosemite National Park 2004; National Park Service 2022). Distributional and statistical distance metrics offer a quantitative means to evaluate progress toward such targets and to assess whether management actions maintain or restore variability within desired bounds. Beyond this case study of fire frequency and severity, these tools can be extended to other ecosystem processes where both the mean state and its variability define resilience.

EMD enables new research into how fire regimes and their changes influence other landscape scale processes. Many ecological and resource management questions can benefit from approaches that characterize differences in statistical, temporal, or spatial distributions as opposed to changes in specific statistical moments. One example for fire science is to examine the hypothesis that diversity of fire over space (pyrodiversity) leads to habitat diversity, and consequently, biodiversity (Martin and Sapsis 1992). Recent work in this theory called for the integration of historical baselines into pyrodiversity research because species presence emerges from a combination of current conditions and historical legacies (Jones and Tingley 2022; Jones et al. 2022). Our study essentially measures how pyrodiversity changed over the last few centuries and can be readily applied to pyrodiversity research (Steel et al. 2021). Beyond the pyrodiversity-biodiversity hypothesis, we see relevant applications to understanding habitat diversity, continuous changes in fire regimes through time, and changes in fire behavior, to name a few (Cansler and McKenzie 2014; Zhang et al. 2020; Cova et al. 2023). Readers are referred to the literature on optimal transport theory for a deeper treatment (Peyré and Cuturi 2020).

Limitations

Our results are sensitive to the assumptions and limitations of the datasets we used, namely LANDFIRE BPS (LANDFIRE 2020), and MTBS (Eidenshrink et al. 2007). LANDFIRE BPS uses expert information, paleoecological evidence, and simulation modeling to estimate historical fire regimes of vegetation groups, and our results reflect their methodological decisions (Barrett et al. 2010; LANDFIRE 2020). For example, LANDFIRE BPS does not report any low severity fire in the biophysical settings in the region south of Yellowstone National Park, likely explaining why we found lower contemporary fire severity despite recent increases in high severity reburns and evidence of low-severity fires in much of the ecosystem (Fig. 5A; Cansler et al. 2018; LANDFIRE 2020; Spies et al. 2018; Turner et al. 2022).

Furthermore, we assume that BPS fire return intervals and fire rotation periods are equivalent at the landscape scale (Johnson and Gutsell 1994; Hargrove et al. 2000; Farris et al. 2010; Swetnam et al. 2011; Haugo et al. 2015). However, specific studies posit that biases in the methods used to estimate fire regime attributes of BPS types may overestimate the historical frequency of low- and mixed-severity fire in dry forests (Baker 2024). To address these concerns, we included the adjustments to the 48 BPS types modified by Baker (2024) in a sensitivity test (Appendix D).With this modification, the percentage of hexels burning less frequently and relatively more severely decreased from 89% to 66% - a measurable effect, but one that doesn't change the key takeaway that most of the western US appears to be burning less frequently and more severely than historical estimates. A full spatial analysis of these differing results is beyond the scope of this study, but we note that the adjusted results show that much of the western Sierra Nevada range are no longer shown as burning less frequently and more severely (Appendix D) than BPS estimates. This is highly contradictory to multiple lines of evidence from this region that show that contemporary wildfires are burning less frequently and relatively more severely based on fire scars (Coppoletta et al. 2024; Parks et al. 2025), aerial photography (Lydersen and Collins 2018), process-based models (Barth et al. 2015), Indigenous oral histories (Stephens et al. 2023), and sediment core records (Klimaszewski-Patterson et al. 2024), all of which support using unmodified BPS fire return intervals as we have done here.

We used MTBS, which only includes fires greater than 404 hectares (Eidenshrink et al. 2007; Picotte et al. 2020), which may introduce a bias in our departure measures towards less frequent, more severe departures (Cansler and McKenzie 2014; Cova et al. 2023). To address this, we ran two tests comparing MTBS data to two California-focused datasets that include small fires from Koontz et al. (2020) and Cova et al. (2023). Overall, severity departures were slightly lower with the inclusion of small fires, but all three datasets yielded similar conclusions that California is burning less frequently and relatively more severe now than it did in the past (see Supplement 2).

Our methods have three main limitations. First, we simulated fire frequency using a binomial model determined by each pixel's MFRI. The frequency model is appropriate for simulating wildfires over periods of time since MFRI can approximately account for the lack of independence between yearly burn probabilities, but a more robust simulation would likely be more accurate and extendable to different time periods (Li et al. 1999; Reed and McKelvey 2002; Moran et al. 2025). Second, we simulated severity with a weighted piecewise uniform distribution. This severity model does not capture gradients in fire severity, so while the classes of severity should be accurate based on our bootstrapped thresholds, the transitions in CBI between classes are simplified (Agee 1993; Sugihara et al. 2018). Finally, we measured departures in fire frequency and severity separately. Fire regimes are made up of many correlated fire attributes (Sugihara et al. 2018). Developing the joint distributions of multiple fire attributes could quantify changes in the covariance between fire attributes and fire regimes more broadly, potentially exposing novel fire regime departures (Parks et al. 2015; Steel et al., 2015).

Despite these limitations, our study is a step towards the development of statistically robust and ecologically meaningful multivariate distributional departure metrics in ecology. Metrics that characterize distributional changes in fire regimes provide a more nuanced characterization of departures than those based on means (Sugihara et al. 2018; Buma et al. 2019). Recognizing changes in the statistical distributions of fire regimes, when combined with land management practices, can highlight opportunities for restoring historical fire dynamics and supporting ecosystem resilience to future disturbances and climate changes.

Fire regime departures of the western US

Forested landscapes of the western US are burning less frequently and more severely today compared to a historical reference period (1600-1880; Fig. 5). Although annual area burned increased across the western US since 1985, contemporary fire frequency is still well below levels indicated by models of 17th-20th century fire regimes based on paleoecological data (Marlon et al. 2012; McClure et al. 2024). This paradoxical observation of rapid contemporary increases in fire activity that still remains below historical levels, is well documented by previous research (Haugo et al. 2019; Hagmann et al. 2021; Williams et al. 2023; Donato et al. 2023). This widespread fire deficit (Parks et al. 2015b) is understood to be increasing the relative incidence of uncharacteristically severe fires across the western US (Haugo et al. 2019; Hagmann et al. 2021; Higuera et al. 2021; Williams et al. 2023; McClure et al. 2024; Povak et al. 2025). Our analyses show that decreases in fire frequency correspond strongly with increases in fire severity, supporting this contention (Fig. 4 and 5).

Areas with high contemporary human land use have the highest departures. We found higher departures in areas of high human footprint, lower public land coverage, and lower Wilderness and National Park coverage (Fig. 5C). These patterns are likely due in part to fire exclusion. Fire exclusion policies have been, and continue to be, implemented in areas with high human footprint due to the risk wildfires pose to community safety and assets (Miller 2006; Wagtendonk 2007; Iglesias et al. 2022; Boerigter et al. 2024). The deficit of wildland fire leads to increasing fuel accumulation, particularly in the sub canopy, and subsequently larger and more severe wildfires which further threaten communities, encouraging further fire suppression (McLauchlan et al. 2020; Higuera et al. 2023; Kreider et al. 2024) – a positive feedback of ecosystem degradation termed the fire suppression paradox (Calkin et al. 2015;

Cohen 2008; Kreider et al. 2024). While there is extensive evidence supporting this explanation, our relatively large hexels may produce departure values that are driven by simple changes in where fires occur (Kreider et al. 2024), rather than an intrinsic change in the fuels (Haugo et al. 2019; Povak et al. 2025).

Federally prioritized landscapes provide another lens through which to assess the relationship between fire regime departure and human influence (Fig. 6). Priority landscapes designated in the Wildfire Crisis Implementation Plan were largely identified based on community vulnerability and capacity to mitigate wildfire hazard (US Forest Service, 2022). Our results show that priority landscapes have higher fire regime departures than non-priority landscapes, in part because of the prevalence of large priority landscapes in California (Fig. 5B), where the highest departure values in the western US occur. Fire regime departure and community risk are seemingly interlinked. We can, however, break the link between human influence and fire regime departures by implementing intentional fire management plans that returns frequent, low intensity fire to fire-prone forests (Ager, Evers, et al. 2021; Barros et al. 2021; Iglesias et al. 2022; Krawchuk et al. 2023; Syphard et al. 2013; North et al. 2024; Dunn et al. 2020).

Our findings, that most ecosystems in the Western US exhibit lower frequency and higher severity fire activity than their historical references, support the use of prescribed and cultural burning, and managed wildfire, alone and in combination with mild-moderate mechanical treatments. These interventions reintroduce low severity fire and reduce fuel loads (Davis et al. 2023; 2024; Hessburg et al. 2005; Kalies and Yocom Kent 2016). Together, these moderate wildfire severity and reduce risk to nearby communities. Lower risk, in turn, eases the social and operational constraints on restoration, allowing managers to reestablish the full spectrum of fire effects, potentially including high-severity patches where appropriate (Miller et al. 2020; Stephens et al. 2020; Donato et al. 2023; Williams et al. 2024; Baker 2024; Davis et al. 2024).

List of abbreviations

EMD: Earth Mover's Distance

MFRI: Mean Fire Return Interval Departure

BPS: BioPhysical Setting

HRV: Historical Range of Variation

MTBS: Monitoring Trends in Burn Severity

CBI: Composite Burn Index

NDVI: Normalized Difference Vegetation Index

FRCC: Fire Regime Condition Class

FFD_{cc}: FRCC Fire Frequency Departure

FSD_{cc}: FRCC Fire Severity Departure

FRD_{cc}: FRCC Fire Regime Departure

FFD: Distributional Fire Frequency Departure

FSD: Distributional Fire Severity Departure

MFRD: Multivariate Distributional Fire Regime Departure

SD: Standard Deviation

IQR: Interquartile range

Availability of data and materials

Additionally, we provide R scripts for the full analysis and each databases analysis at https://github.com/souma4/Fire_Regime_Departure. We provide analyzed hexels, wilderness areas, protected areas, firesheds, HUC8 and HUC10 datasets as GeoPackage files (gpkg, similar to GeoJSON) at the following database https://osf.io/vak2d/?view_only=e501253436074599a93dbb5cb627de47. Within each GeoPackage, we report all statistics described in Supplemental 1. In tandem with each dataset, we provide a database of every dataset, with each dataset containing maps of BPS, fire frequency, and average fire severity, and figures that show the historical and contemporary frequency and severity distributions for all landscapes within.

Ethics declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Authors contributions

Conceptualization: J.R.C., S.A.P., and S.Z.D. Methodology: J.R.C., S.A.P., T.J.H, C.A.C., S.Z.D. Formal Analysis: J.R.C. Data Curation: J.R.C., S.A.P. Visualization: J.R.C., S.A.P., S.Z.D., T.J.H., C.A.C. Writing---original draft: J.R.C. Writing---review and editing: S.Z.D., S.A.P., C.A.C., T.J.H.

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Figure Captions

Figure 1: Conceptual diagram of fire regime change in a historically frequent fire ecosystem when observed over 37-year historical and contemporary periods. A) Transitioning from a frequent fire system to an infrequent fire system due to fire exclusion leads to homogenization in spatial patterns of fire occurrence. B) As a result, the statistical distributions of fire frequency during historical and contemporary are different. However, the contemporary and historical periods have the same mean fire frequency, marked by the dashed line. Means do not characterize the homogenization of the fire frequency distribution through time.

Figure 2: Workflow of our analysis within a single landscape polygon. Circles represent numeric outputs while rectangles are operations. We sampled forested pixels (in green) and performed the operations in the light blue box for each pixel. Then we converted those results to normalized distributions of fire frequency and severity for historical and contemporary time periods. From these distributions, we calculated EMD between historical and contemporary fire frequency departure (FFD) and fire severity departure (FSD), which are combined into a multivariate fire regime departure (MFRD) index. This analysis is replicated 100 times for each landscape, and our primary summaries are the median FFD, FSD, and MFRD.

Figure 3: Relationship between percent tree mortality (y-axis) and CBI (x-axis) from Parks et al. (2023). LANDFIRE classes low severity as < 25% tree mortality, mixed severity as between 25% and 75%, and high severity as > 75%. We show the median logistic regression curves with thresholds for low to mixed (T_{lm}) and mixed to high (T_{mh}) marked by vertical dashed lines and median and 95% bootstrapped confidence intervals by the error bars. Median and 95% confidence intervals for T_{lm} and T_{mh} are 1.56[1.33, 1.72], and 2.01[1.92, 2.17], respectively. AUC is the mean bootstrapped AUC. Additional accuracy statistics are in Appendix B.

Figure 4: Scatter plot of signed fire frequency (FFD; x-axis) and severity (FSD; y-axis) departures for hexels (≥ 10% forested) and states in the western US. Colored symbols show the 20% trimmed mean and 95% CIs for each state within our study area. Quadrants are labeled based on the average direction of change in each attribute. Points further away from (0,0) are more departed. Eighty-nine percent of hexels burned less frequently and more severely during the contemporary period compared to their historical baseline.

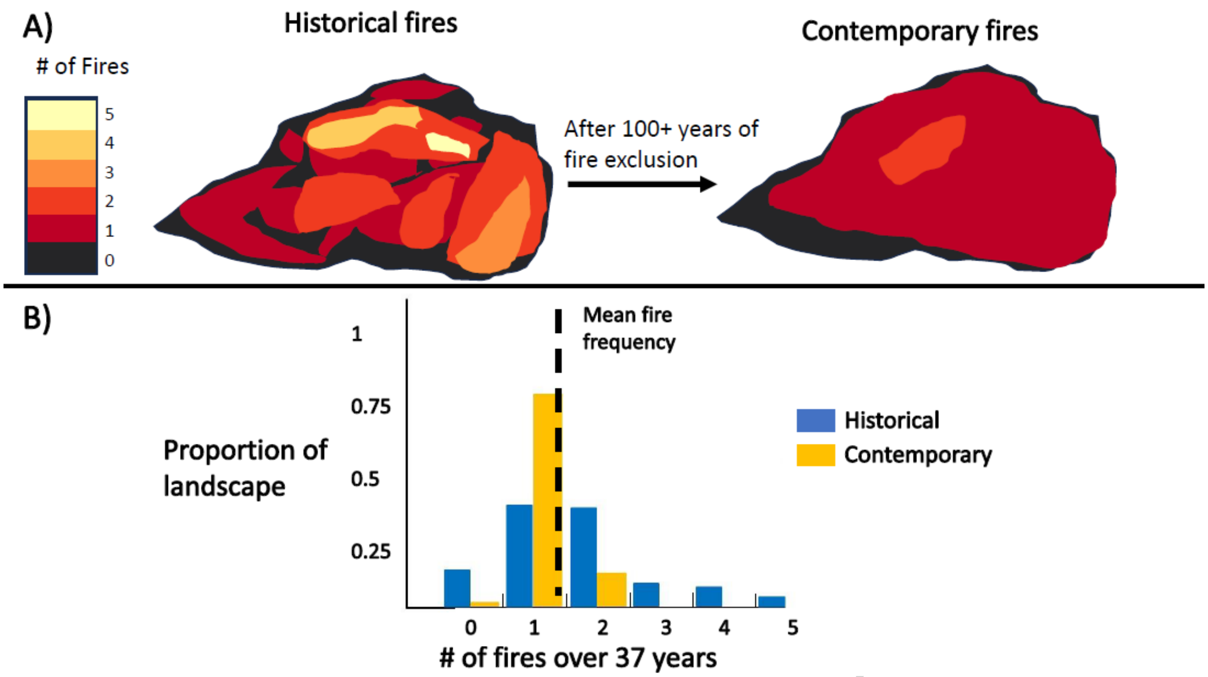
Figure 5: A) Map of signed fire frequency (FFD) and severity departures (FSD) for hexels across western US forested areas. Colors further away from the center (white) are more departed. Color breaks are the absolute 33rd percentiles in each dimension (to ensure negative and positive color breaks are evenly spaced). B) Map of the multivariate distributional fire regime departure (MFRD) for hexels across forested areas within the western US. Larger values represent larger departures. We also display hexels that did not burn during the contemporary period in grey or blue-purple, where blue-purple stands for a frequency departure greater than 1. California has significantly higher departures than other states (linear contrasts in Appendix C). C) Mean and 95% confidence interval hexel multivariate fire regime departure (MFRD) plotted with multiple binned human land use metrics. Left to right are the average human footprint within a hexel, percentage covered by public lands, and percentage covered by Wilderness & National Park Service. In all analyses, increased human footprint, decreased public land coverage, and

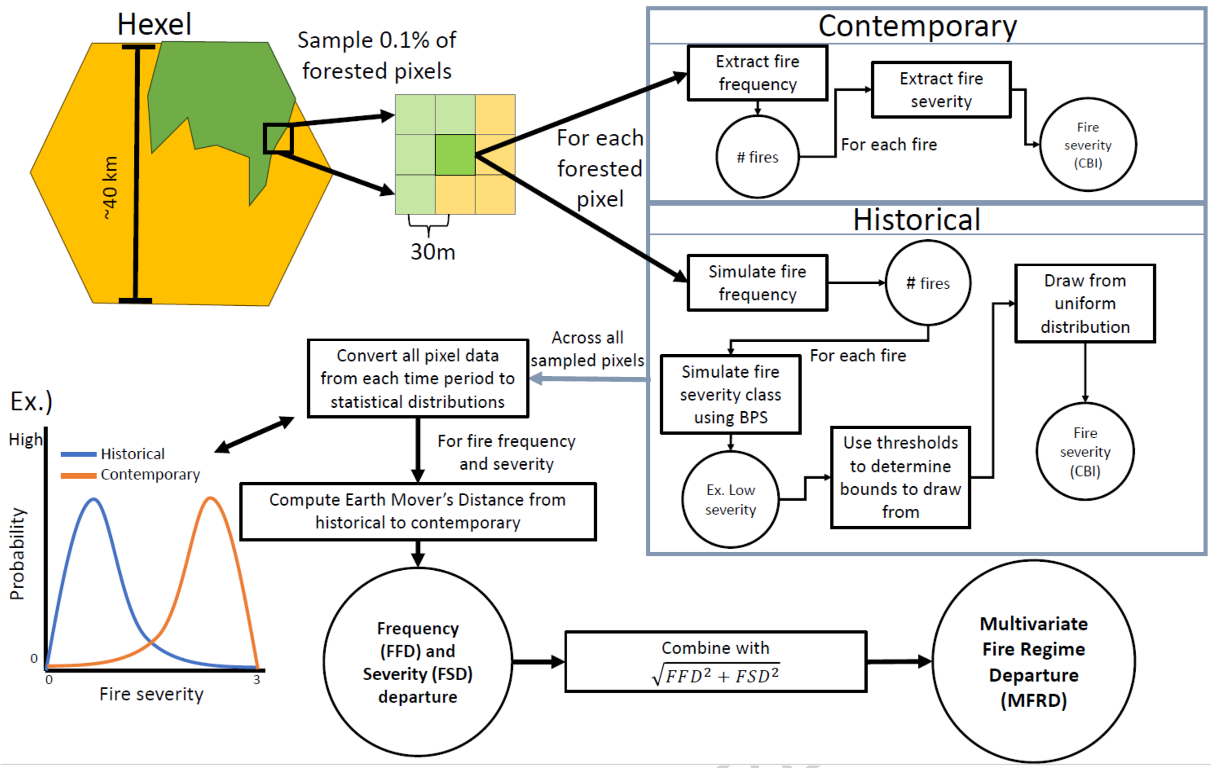
decreased coverage by protected lands resulted in higher departures (α= 0.01, full pairwise tests are available in Appendix C).

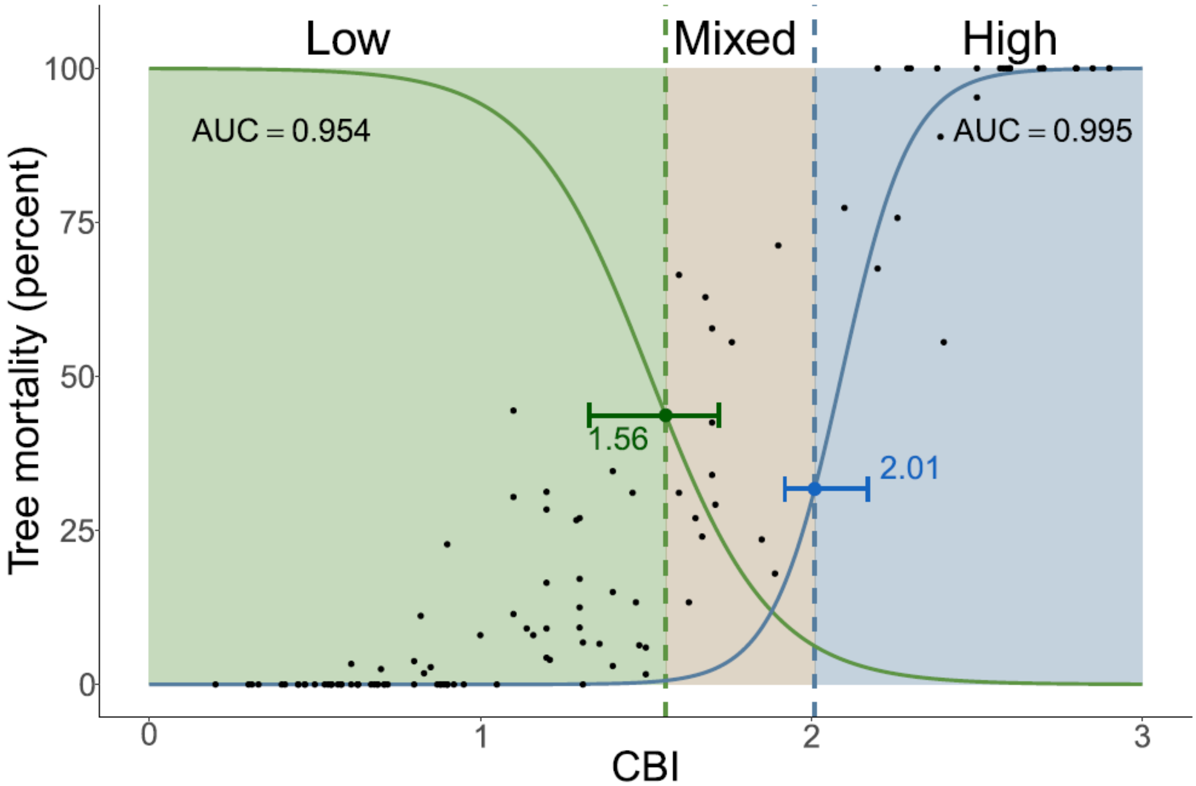
Figure 6: A) Map of firesheds with the Wildfire Crisis Strategy priority landscapes (WCS landscape) outlined in black. Firesheds highlighted in red are those with greater than 50% of their area within a WCS landscape. B) Boxplot of priority and nonpriority firesheds, error bars denoting the 95% Confidence Intervals on 20% trimmed means.

Figure 7: Difference between the relative change for the proposed distributional metrics (in percentile) and the mean based FRCC metrics (in percentile) for fire frequency, severity, and regime departures (distributional – mean). Positive values are locations where the proposed EMD-based metrics reported a larger departure relative to the FRCC. Values further away from zero have the largest dissimilarity from FRCC.

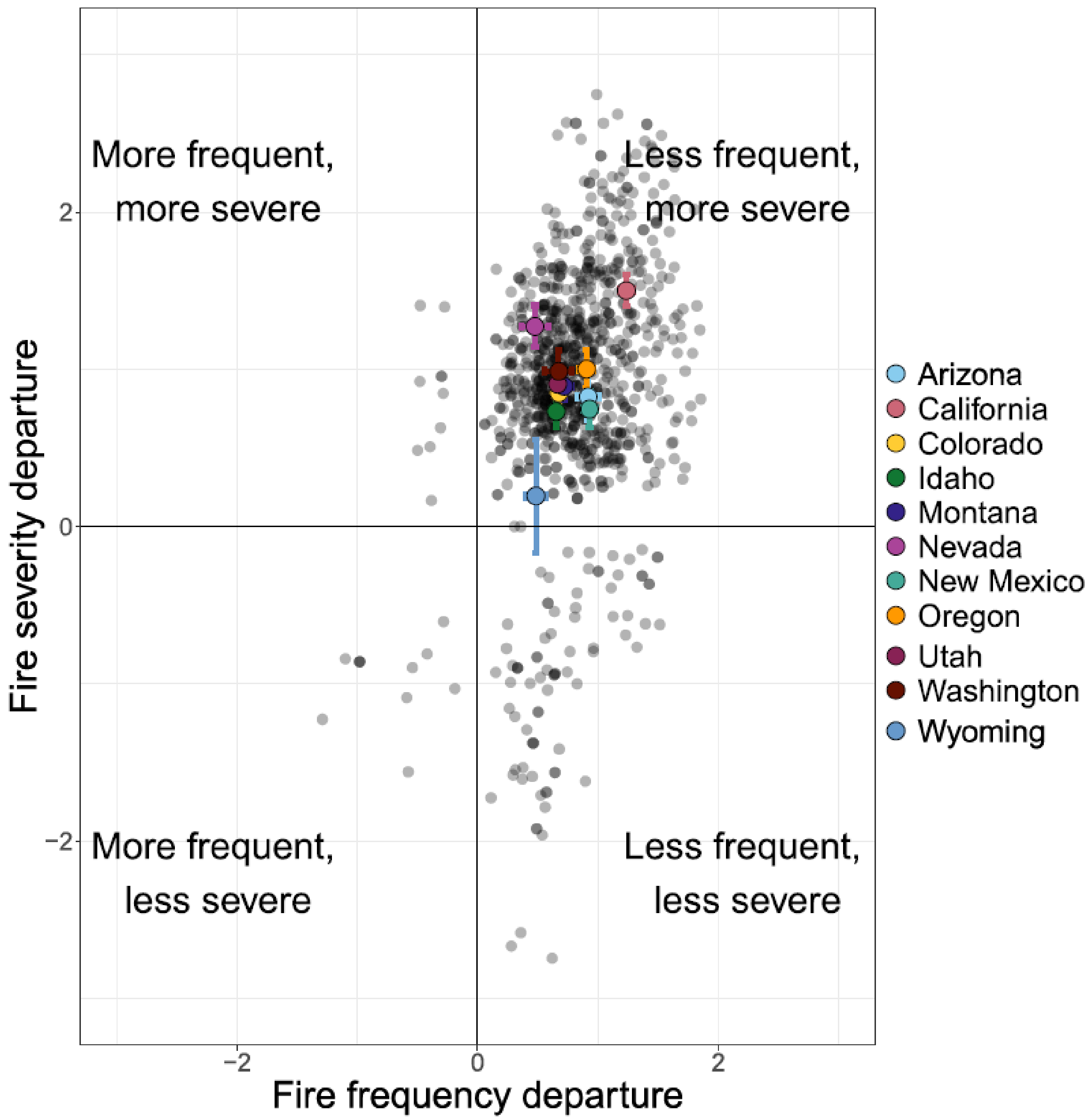
Figure 8: A) Inset map of the study areas and a stem plot illustrating differences between mean-based fire frequency relative departure (Fire Regime Condition Class; relative to the western U.S.) and distributional departure based on Earth Mover's Distance (EMD). B) Fire frequency distributions for Kalmiopsis and Olympic National Parks, respectively. Each semi-transparent line represents one of the first 30 simulation runs (out of 100, reducing clutter), illustrating the non-normal variance in distributions. Dotted vertical lines show mean fire frequency, corresponding to historical and contemporary MFRIs: 13 and 19 years for Kalmiopsis; 309 and ~17,000 years for Olympic. Kalmiopsis appears to have shifted from a frequent, variable regime to an infrequent, simplified one—poorly captured by mean-based metrics. In contrast, the distributions of Olympic remain similar despite large differences in MFRI, highlighting how EMD-based metrics can be resistant to large MFRI differences in infrequent fire systems.

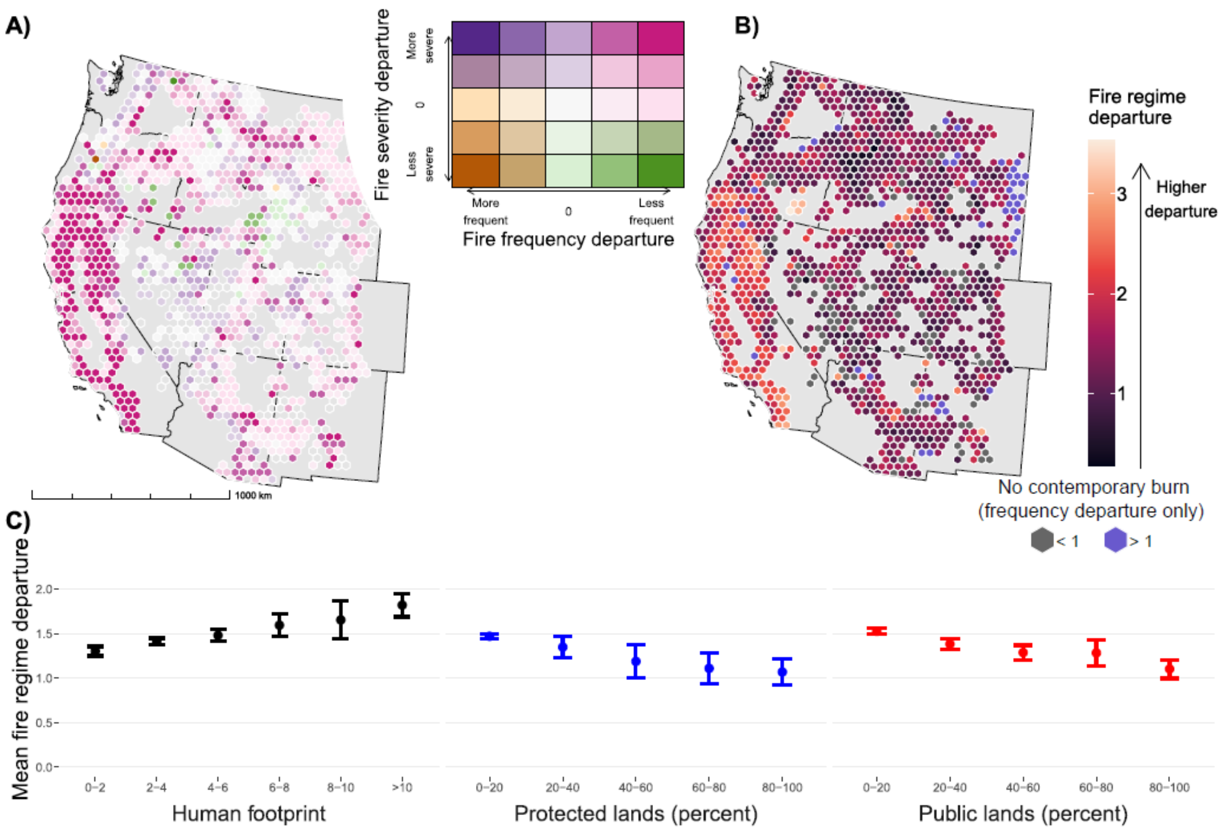

A)
Historical fires
Contemporary fires
# of Fires
5
4
3
2
1
0
After 100+ years of fire exclusion
B)
Mean fire frequency
1
0.75
0.5
0.25
Proportion of landscape
Historical
Contemporary
0
1
2
3
4
5
# of fires over 37 years

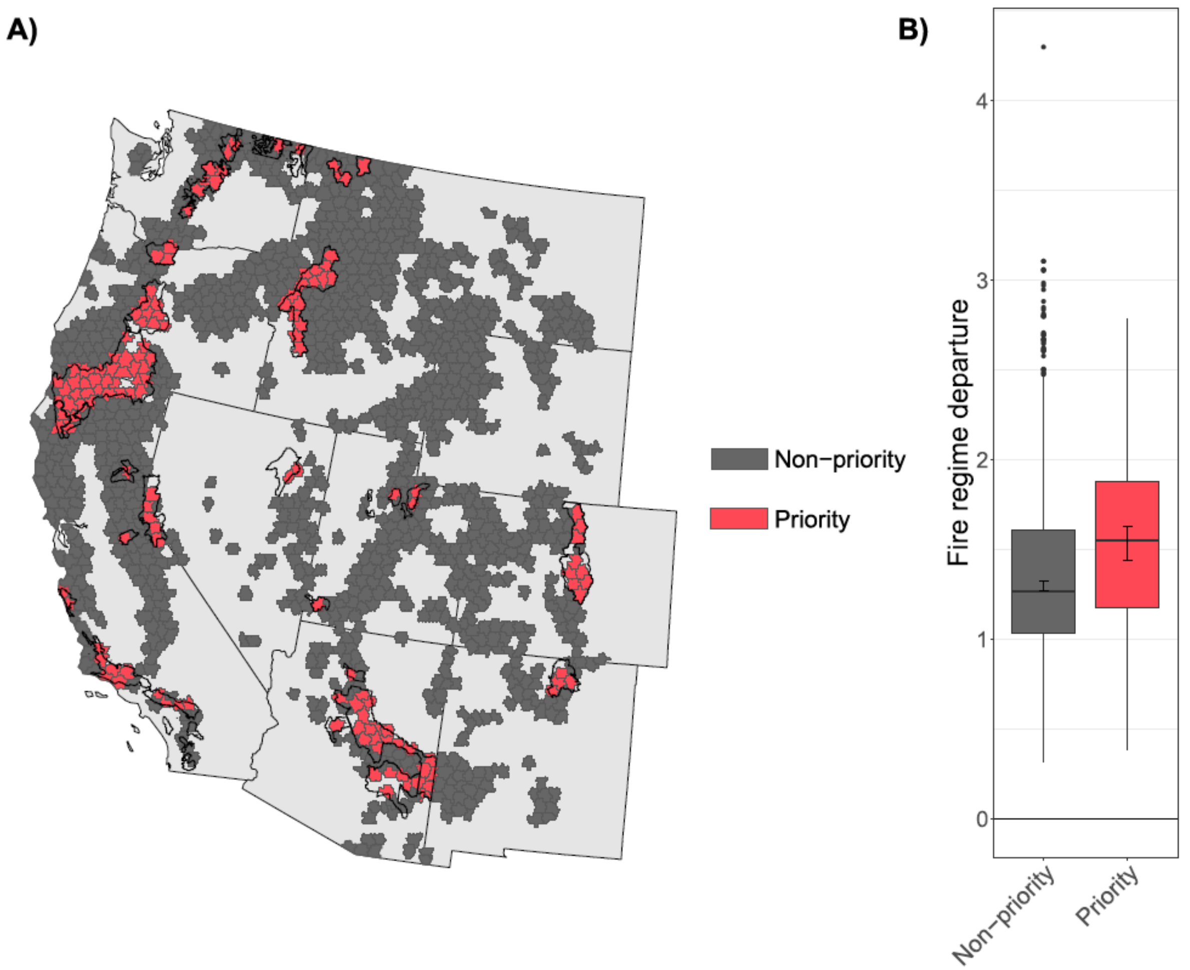

Hexel
~40 km
Sample 0.1% of forested pixels
30m
For each forested pixel
Contemporary
Extract fire frequency
fires
For each fire
Extract fire severity
Fire severity (CBI)
Historical
Simulate fire frequency
fires
For each fire
Simulate fire severity class using BPS
Ex. Low severity
Use thresholds to determine bounds to draw from
Draw from uniform distribution
Fire severity (CBI)
Across all sampled pixels
Convert all pixel data from each time period to statistical distributions
For fire frequency and severity
Compute Earth Mover's Distance from historical to contemporary
Frequency (FFD) and Severity (FSD) departure
Combine with $\sqrt{FFD^2 + FSD^2}$
Multivariate Fire Regime Departure (MFRD)
Ex.)
High
Historical
Contemporary
Probability
0
0
3
Fire severity

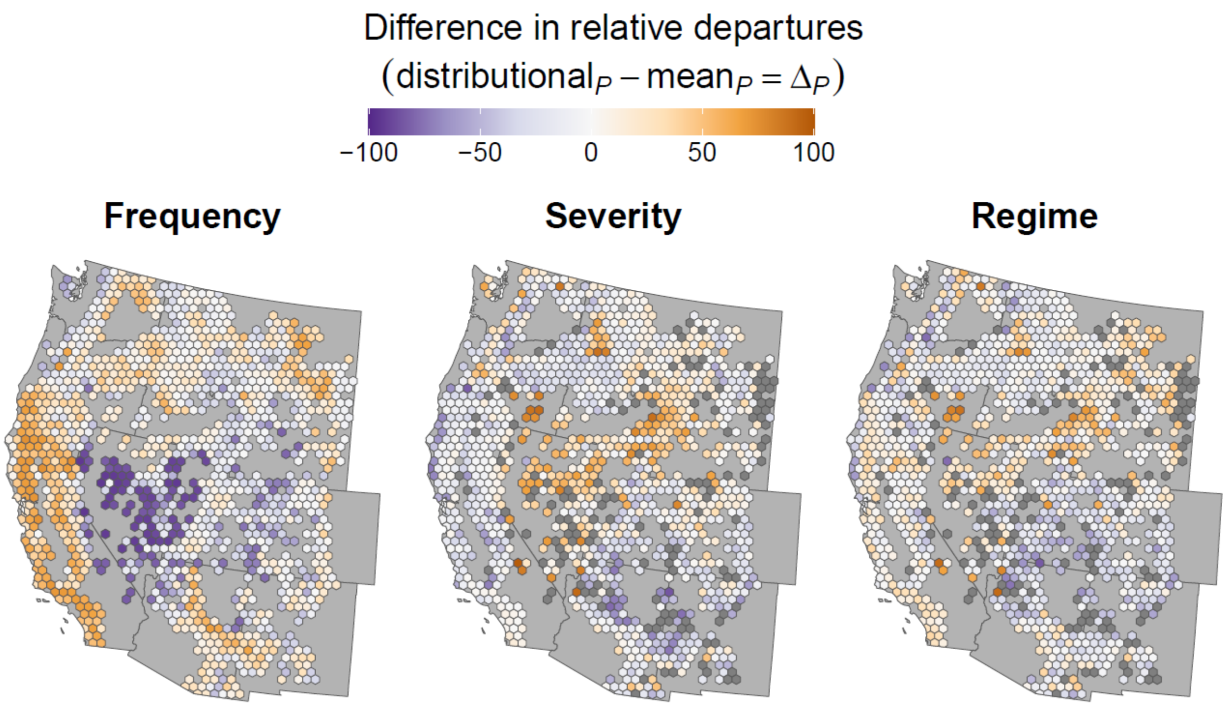


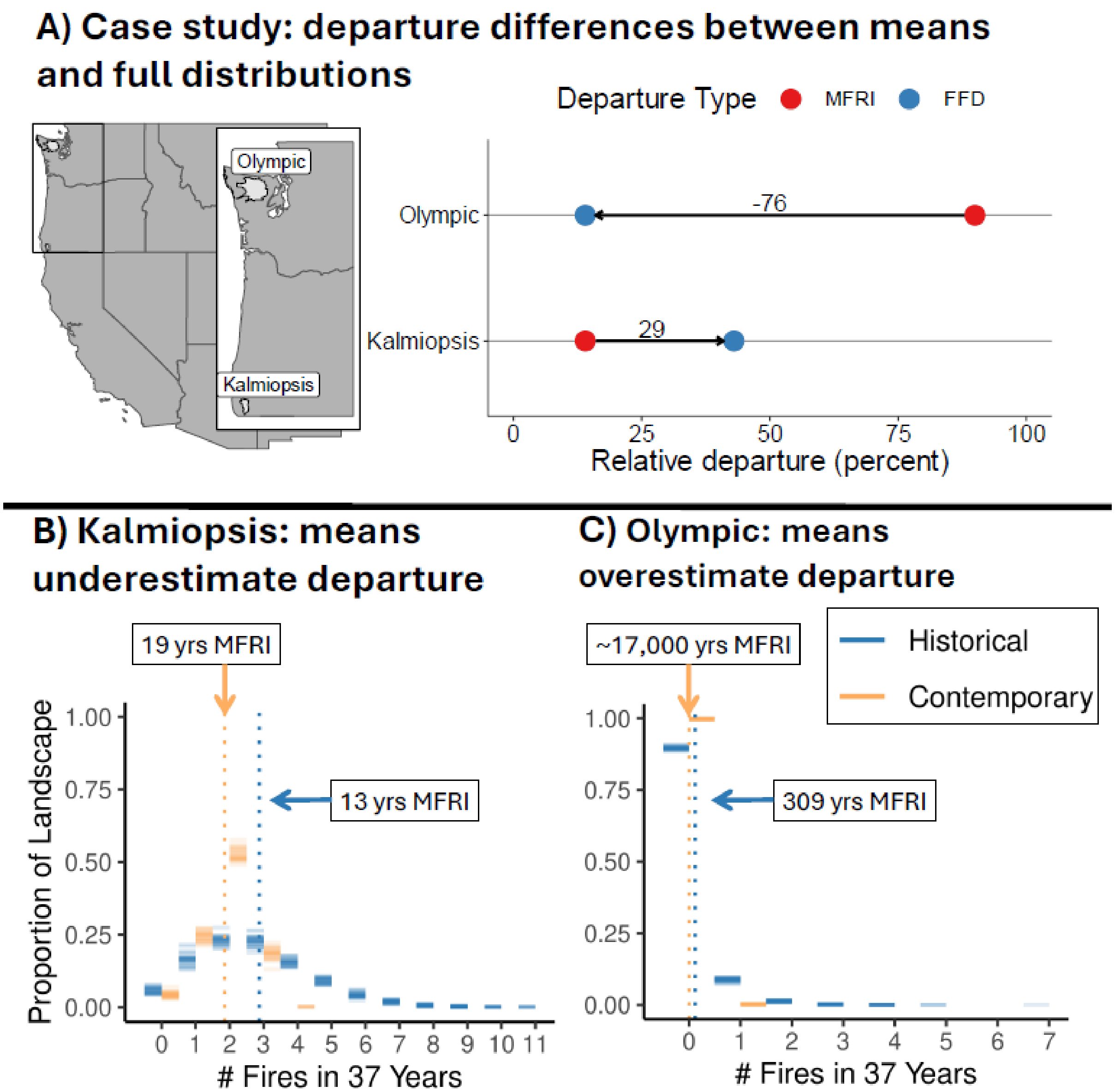
Low
Mixed
High
AUC = 0.954
AUC = 0.995
1.56
2.01
100
75
50
25
0
Tree mortality (percent)
0
1
2
3
CBI


More frequent, more severe
Less frequent, more severe
More frequent, less severe
Less frequent, less severe
2
0
−2
−2
0
2
Fire severity departure
Fire frequency departure
Arizona
California
Colorado
Idaho
Montana
Nevada
New Mexico
Oregon
Utah
Washington
Wyoming


A)
Fire severity departure
More severe
0
Less severe
More frequent
0
Less frequent
Fire frequency departure
1000 km
B)
Fire regime departure
3
2
1
Higher departure
No contemporary burn
(frequency departure only)
< 1
> 1
C)
Mean fire regime departure
2.0
1.5
1.0
0.5
0.0
0–2
2–4
4–6
6–8
8–10
>10
Human footprint
0–20
20–40
40–60
60–80
80–100
Protected lands (percent)
0–20
20–40
40–60
60–80
80–100
Public lands (percent)


A)
B)
Non−priority
Priority
Fire regime departure
0
1
2
3
4
Non-priority
Priority


Difference in relative departures
$(\text{distributional}_P - \text{mean}_P = \Delta_P)$
−100
−50
0
50
100
Frequency
Severity
Regime


A) Case study: departure differences between means and full distributions
Departure Type
MFRI
FFD
Olympic
Kalmiopsis
-76
29
0
25
50
75
100
Relative departure (percent)
B) Kalmiopsis: means underestimate departure
19 yrs MFRI
13 yrs MFRI
Proportion of Landscape
1.00
0.75
0.50
0.25
0.00
0 1 2 3 4 5 6 7 8 9 10 11
Fires in 37 Years
C) Olympic: means overestimate departure
~17,000 yrs MFRI
309 yrs MFRI
Historical
Contemporary
0 1 2 3 4 5 6 7
Fires in 37 Years