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Research Note

Mapping fire regime ecoregions in California

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Abstract. The fire regime is a central framing concept in wildfire science and ecology and describes how a range of wildfire characteristics vary geographically over time. Understanding and mapping fire regimes is important for guiding appropriate management and risk reduction strategies and for informing research on drivers of global change and altered fire patterns. Most efforts to spatially delineate fire regimes have been conducted by identifying natural groupings of fire parameters based on available historical fire data. This can result in classes with similar fire characteristics but wide differences in ecosystem types. We took a different approach and defined fire regime ecoregions for California to better align with ecosystem types, without using fire as part of the definition. We used an unsupervised classification algorithm to segregate the state into spatial clusters based on distinctive biophysical and anthropogenic attributes that drive fire regimes – and then used historical fire data to evaluate the ecoregions. The fire regime ecoregion map corresponded well with the major land cover types of the state and provided clear separation of historical patterns in fire frequency and size, with lower variability in fire severity. This methodology could be used for mapping fire regimes in other regions with limited historical fire data or forecasting future fire regimes based on expected changes in biophysical characteristics.

Additional keywords: classification, ecosystems, fire frequency, fire history, global change, land cover, pyrogeography, scale.

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Introduction

Central to wildfire science is the concept of the fire regime, which describes the long-term range of variation inherent in wildfire characteristics in a given ecosystem, including fire frequency, size, severity, seasonality and pattern (Bond and van Wilgen 1996). In addition to describing the characteristics of wildfires over time, the fire regime concept is also used to distinguish how fires vary geographically and in different ecosystems.

Defining fire regimes for different regions provides an important framework for guiding management and assessing risks to human communities and ecological systems. This is because, despite the natural stochasticity of wildfire, understanding a region's characteristic fire regime provides a reference for what can be expected and in turn, for understanding when the system is behaving unexpectedly (Safford and Van de Water 2014).

Given the ubiquity of the fire regime concept in fire science and ecology, several efforts have been made to distinguish fire regimes geographically (Morgan *et al.* 2001; Keane *et al.* 2003; Falk *et al.* 2007), and the term 'pyrogeography' has emerged as a framing concept to describe the geographical distribution of fire relative to its human and biophysical drivers (Bowman *et al.* 2011). Maps of different fire regime regions provide guidance to managers relative to which strategies may be most effective for balancing fire risk reduction with natural resource protection. Maps of fire regime regions may also be helpful for scientific research endeavours meant to assess drivers of altered fire regimes (Keeley and Pausas 2019) and to project potential future scenarios relative to an appropriate baseline. For example, recent work provides evidence that climate–fire relationships vary from region to region, likely due to differences in the effects of human and biophysical drivers on fire initiation and behaviour (Littell *et al.* 2009; Keeley and Syphard 2017; Syphard *et al.* 2017). Thus, assessing historical or projecting future fire activity should be performed relative to the limits of the fire regime under consideration.

While fire regimes have been delineated geographically, those efforts have focused on identifying spatial clusters where there are natural groupings of fire regime characteristics. For instance, the LANDFIRE program in the USA provides nationwide consistently mapped fire regime data products with fire regime groups based on fire severity and frequency (Rollins 2009). Bradstock (2010) characterised the biogeography of fire across Australia based on fire regime characteristics that included biomass, availability to burn, fire spread and ignitions.

Archibald *et al.* (2013) used a different suite of fire characteristics, including frequency, intensity, season and extent to define global patterns of fire regimes, or 'pyromes', in their terminology. Others have used a similar approach (Moreno *et al.* 2014).

The Archibald *et al.* (2013) analysis showed that different biomes and climates could produce the same fire regime. For example, the low-frequency/high-severity fire regime group in LANDFIRE combines deserts, very wet forests and high-elevation forests. Whitlock *et al.* (2010) provided a paleoecological perspective that indicated this approach of defining regimes based on fire characteristics should be reconsidered because fire regimes change within the same biome over time. They cautioned that this characteristic would be problematic when making future forecasts of fire regimes, which is especially critical given expected changes in vegetation over time (Syphard *et al.* 2017). In addition to issues related to combining very different ecosystem types, delineating fire regime ecoregions using fire parameters to define them may be limited by the quality, scale and availability of different types of fire data. For instance, there is better information and mapping for fire frequency than for other fire characteristics (Morgan *et al.* 2001).

We took a different approach and defined fire regime ecoregions for California by spatially segregating the state into natural clusters with distinctive biophysical and anthropogenic attributes, and then evaluated how well these ecoregions compared in terms of fire regimes – without using fire as part of the ecoregion definition. That is, instead of using fire to drive the classification, we interpreted the classification in terms of how well different regions distinguished historical characteristics of wildfire. This approach highlights the important drivers of fire regimes and produces clusters that are better aligned with a full range of ecosystem characteristics that, when combined, manifest in different spatial and temporal patterns of wildfire. This approach could also improve upon fire regime forecasting by accounting for changes in the drivers of altered fire regimes.

We intend this classification to be useful for framing scientific analysis in which interpretation depends upon characteristics of region-specific fire regimes. This mapping approach may also be useful for decision-makers looking to prioritise management actions in line with a region's distinctive fire regimes. California is a heterogeneous state with diverse ecosystems and fire regimes and we offer this digital fire ecoregion map as a potentially useful tool for interested stakeholders.

Methods

Our overall approach was to first develop a statewide map classification using a database of spatial layers representing a wide range of factors associated with differentiating fire regimes. After creating several versions of these maps, we then used available fire data to explore the fire regimes within these regions. We assembled a geographical dataset with variables representing a range of topographic, climatic, vegetation and anthropogenic variables that have been significantly associated with geographical variation in California fire regimes (Barbour *et al.* 2007) (Table 1). All variables were numeric, and we normalised the grids so values fell within a range of 0–100. This normalisation ensured that large differences in numeric ranges of the data would not disproportionately weight any variable over the others. We also resampled all grids to match the resolution of the climate data, which was 270 m.

After assembling all geographical data layers, we used ENMTools (Warren *et al.* 2010) to calculate a pairwise correlation matrix for all variable combinations. To perform the classification, we used a K-means ISODATA clustering algorithm (Ball and Hall 1965) with ArcGIS software (ESRI, Redlands, CA) to derive classified maps. The ISODATA algorithm is an unsupervised clustering approach, meaning it discovers the underlying structure of the data without preconceived labels or definitions. The algorithm works by iteratively assigning grid cells to one of a specified number of classes based on its similarity to class means in multidimensional attribute space, resulting in a set of maximally homogeneous and distinctive classes of varying size. Given that the algorithm defines clusters based on similarity of environmental characteristics, the resulting mapped classes are not necessarily adjacent. We specified the model to iterate 20 times through the maps to optimise assignment and reassignment of grid cells to clusters based on recalculated cluster means for each iteration. We evaluated 6–8 clusters using variables uncorrelated at or above $r = 0.70$ and $r = 0.80$.

For all mapped classes, we used a zonal statistics algorithm to extract mean values for historical fire count, fire size and expected fire severity (variables described in Table 1). We then compared maps by calculating the standard deviation of mean values, providing a measure of class variability. We also tabulated the area and proportion of different land cover types within ecoregion classes to visually compare class separability. We purposely excluded vegetation type in our classification process, in part because map classifications can be subjective; however, vegetation class may be an indicator of differences in fire regimes (Wells *et al.* 2004; Davis and Borchert 2006).

Results

Of the fire regime ecoregion maps that we generated, there were larger differences among the standard deviations of the maps, representing differences in class separability, for fire frequency and size than for fire severity; the map with the highest standard deviation for mean fire frequency and mean fire size was the one with eight classes and variables correlated at $r = 0.7$ (Table 2, map shown in Fig. 1*a*; mean variable values in Appendix 1). This was also the map with the lowest standard deviation in the means of fire severity in the classes. The means of fire severity for all maps fell within the range of 2 and 3 out of a classification ranging from 1 to 4.

In the displayed map, fire frequency and fire size were both highest in ecoregions 5 and 8 (Table 2, Fig. 2*b, c*). Ecoregion 5 was dominated primarily by herbaceous, lowland chaparral and sage scrub and hardwood woodland vegetation, and occurred mostly along the coastal and Sierra Nevada foothills (Fig. 2*d*). Region 8, with the highest frequency and size, was dominated more by conifer, along with shrub and hardwood forest, and was smaller and more widely geographically dispersed (Fig. 2*a–d*). The two ecoregions with the lowest fire frequency were regions 3 and 4, largely representing the desert south-western portion of the state and the coastal urban and central valley agricultural areas respectively (Table 2, Fig. 2*a–d*). Fire size was much larger in region 3 than in region 4.

Table 1. Variables used in the classification and evaluation of fire regime ecoregions in California
FPA-FOD, fire program analysis fire-occurrence database; NDVI, normalised difference vegetation index

Category	Data layer	Description	Source	Used to classify
Fire	Historical frequency	Mean count of fires in each cell, averaged across all cells within fire regime ecoregion 1978–2015	http://frap.fire.ca.gov/data/frapgisdata-sw-fireperimeters_download	
	Severity	Historical severity class (i.e. effect on landcover) for wildfire disturbance 2006–2016. Classes ranked numerically (1–4) for unburned/low, low, medium and high severity and averaged per fire regime ecoregion within disturbance footprints	https://www.landfire.gov/hdist.php	
	Size	FPA-FOD, 1992–2015, inverse distance weighted spatial interpolation based on fire size attribute (ha)	https://www.fs.usda.gov/rds/archive/Product/RDS-2013-0009.4/	
Terrain	Elevation	Height above sea level (m)	https://www.landfire.gov/elevation.php	X
	Topographic heterogeneity	Range of elevation values within 810-m radius from centre cell (0–1)	Nature Serve (https://databasin.org/datasets/1f86100938b544a3b6361eee6ac05945)	X
Climate	Annual precipitation	Mean sum over calendar year (mm), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
	Summer precipitation	Mean sum over June, July, August (mm), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
	Annual minimum temperature	Mean minimum temperature of December, January, February (°C), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
	Annual maximum temperature	Mean maximum temperature over June, July, August (°C), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
	Actual evapotranspiration	Total annual water evaporated from surface and transpired by plants (mm), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
	Climatic water deficit	Annual evaporative demand exceeding water availability (mm), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
	Snow water equivalent	Amount of water contained within snowpack (mm), 1981–2010	http://climate.calcommons.org/dataset/2014-CA-BCM	X
Vegetation	NDVI annual minimum	30-year means of annual minimum NDVI, Landsat TM, 1984–2010 (−1 – 1)	http://climateengine.org/data	X
	NDVI annual maximum	30-year means of annual maximum NDVI, Landsat TM, 1984–2010 (−1 – 1)	http://climateengine.org/data	X
	Vegetation type	Habitat and land cover types spanning 1990–2014	https://frap.fire.ca.gov/mapping/gis-data/	
Land use	Housing density	Derived from US Department of Commerce, US Census Bureau partial block groups, 2000, units per square km	http://silvis.forest.wisc.edu/data/housing-block-change/	X
	Distance to roads	Derived Euclidean distance to TIGER line files 2015, US Department of Commerce, US Census Bureau (m)	https://www.census.gov/geo/maps-data/data/tiger-line.html	X

Discussion

In contrast to previous approaches to defining fire regimes using fire statistics (e.g. Bradstock 2010; Archibald *et al.* 2013; Moreno *et al.* 2014), we adopted an unsupervised clustering approach to spatially delineate fire regime ecoregions using variables long known to drive fire patterns and behaviour (Bowman *et al.* 2011). Subsequent quantification of historical fire frequency and size across regions, in addition to variability in vegetation type across classes, showed substantial separation for most maps and cluster combinations. Fire severity was more uniformly distributed among classes. These differences across classes indirectly demonstrate the extent to which vegetation, climate, human presence and geomorphology are related to fire regimes in California and this approach provides a new means of geographically distinguishing fire regimes. Given widespread limitations in fire mapping and statistics (Morgan *et al.* 2001; Syphard and Keeley 2016), deriving classified maps from fire regime drivers may provide a more robust means of delineating fire regime variation. This approach could be replicated in any fire-prone area to account for the unique combinations of fire regime drivers in different regions.

The ecoregion concept has long been acknowledged and incorporated into research and management in ecology (Bailey 1980; Omernik 1987); one useful framework for ecoregion classification has been to define a spatial hierarchy of levels, or boundaries, consisting of different numbers of nested regions (Omernik and Griffith 2014). Although we compared limited combinations of 6–8 classes and two correlation coefficients, other classifications could extend this hierarchical framework to include additional levels of fire regime classes or alternative variable combinations to fit different management or research objectives. Most ecoregional classifications are mapped using discrete boundaries around contiguous areas (e.g. Omernik 1987), but we provide the map as is, reflecting the inherent

Table 2. Fire statistics for eight fire regime ecoregion maps consisting of 6-8 classes and two correlation cut-off points in the unsupervised clustering analysis

The bold text shows standard deviations. Fire statistics are described in Table 1

Ecoregion number	Mean frequency (number fires per cell)	Mean frequency (number fires per cell)	Ecoregion number	Mean size (ha)	Mean size (ha)	Ecoregion number	Mean severity class (1–4)	Mean severity class (1–4)
	$r = 0.70$	$r = 0.80$		$r = 0.70$	$r = 0.80$		$r = 0.70$	$r = 0.80$
1	0.254	0.262	1	299.196	261.453	1	2.286	2.361
2	0.259	0.250	2	284.217	123.425	2	2.304	2.060
3	0.063	0.017	3	137.415	136.232	3	2.095	2.028
4	0.094	0.179	4	74.746	107.803	4	2.118	2.062
5	0.698	0.594	5	319.667	242.423	5	2.389	2.504
6	0.358	0.239	6	121.203	146.299	6	2.548	2.479
7	0.233	0.802	7	166.321	485.295	7	2.371	2.467
8	0.978	0.591	8	594.470	342.654	8	2.561	2.504
	0.314	**0.265**		**166.512**	**131.527**		**0.173**	**0.219**
1	0.257	0.257	1	260.033	268.398	1	2.329	2.342
2	0.019	0.012	2	132.590	119.519	2	2.033	2.017
3	0.111	0.186	3	88.243	120.014	3	2.106	2.077
4	0.687	0.586	4	300.099	240.494	4	2.389	2.530
5	0.393	0.260	5	166.796	152.377	5	2.443	2.510
6	0.234	0.546	6	157.418	370.810	6	2.410	2.343
7	0.876	0.652	7	566.218	368.634	7	2.582	2.525
	0.310	**0.239**		**161.847**	**108.650**		**0.194**	**0.213**
1	0.263	0.256	1	247.359	252.097	1	2.352	2.348
2	0.023	0.024	2	136.473	135.466	2	2.036	2.038
3	0.187	0.177	3	114.806	114.849	3	2.129	2.067
4	0.617	0.704	4	261.195	307.766	4	2.456	2.465
5	0.248	0.311	5	170.946	208.082	5	2.451	2.532
6	0.792	0.668	6	475.859	378.633	6	2.525	2.508
	0.289	**0.273**		**131.990**	**101.249**		**0.198**	**0.222**

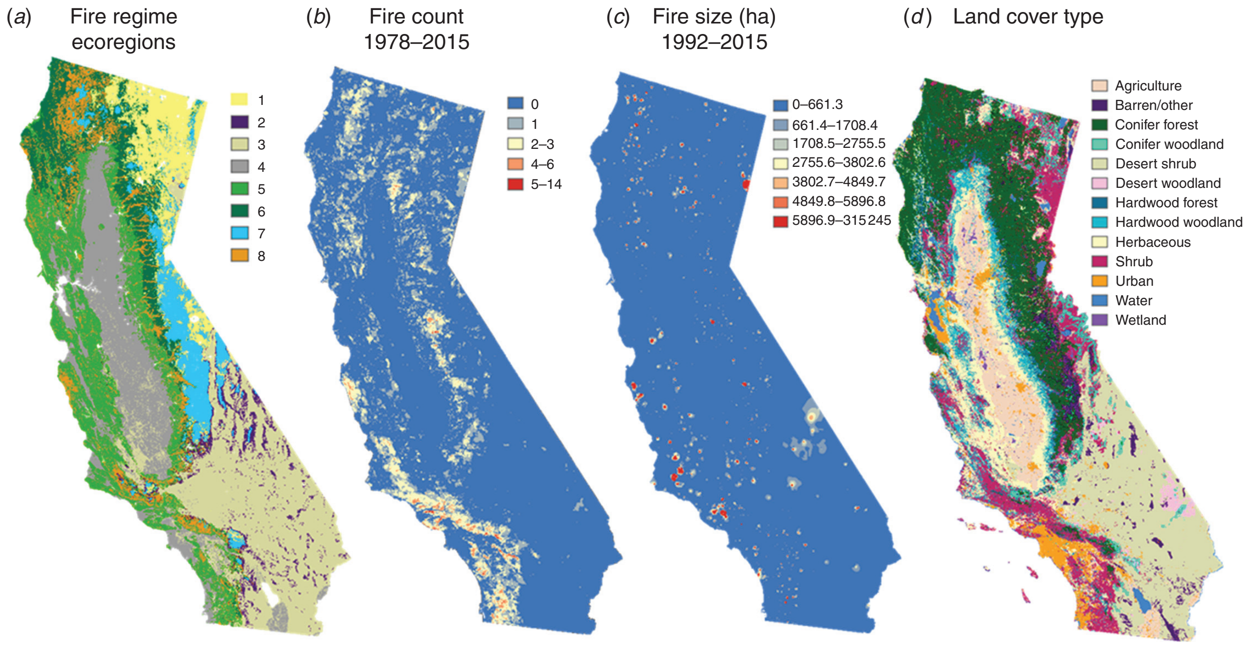

Fig. 1. Maps showing (*a*) fire regime ecoregions with variables correlated at $r \leq 0.7$; (*b*) historical fire count, (*c*) historical fire size and (*d*) land cover type in California.

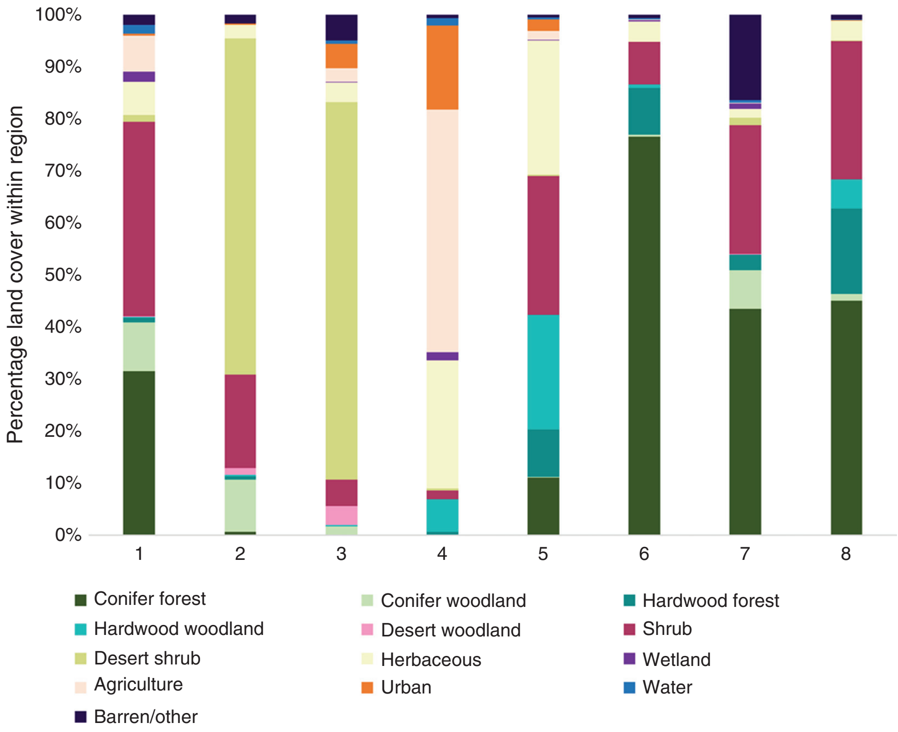

Fig. 2. Percentage of land cover within the eight ecoregions of the California fire regime map with variables correlated at $r \leq 0.70$.

geographical heterogeneity that distinguishes fire regimes. For research or management applications that necessitate discrete boundaries, different smoothing algorithms could be applied to the map. Otherwise, one option for spatial analysis would be to assign the majority class of fire regime ecoregion to different maps of interest. For example, an analysis of the role of fire weather or climate in driving historical fire activity could be segregated into different analyses to account for differences in fire regimes and the majority fire ecoregion type could be assigned to each fire perimeter across the entire extent of analysis.

Some of the independent data, such as climate and the normalised difference vegetation index, represent averages over an approximate 30-year time period, from 1980 to 2010, with the map of housing density falling in between that range. Therefore, analysis or management decisions deriving from this classification should be considered in this temporal context, given how global fire and vegetation patterns are rapidly changing (Franklin *et al.* 2016). Nevertheless, fire regimes are the product of long-term spatial and temporal variations in fire and most input variables were either static or slowly varying; thus, analyses extending slightly beyond this temporal window are likely robust.

One of the most important reasons for performing analysis or making management decisions according to specific fire regimes is that empirical relationships between fire and its drivers are not stationary. Assuming stationarity across regions that encompass widely varying fire regimes could result in analyses that mask or confound empirical relationships or management actions that produce unintended outcomes. Accounting for fire regime ecoregions could also be useful for ecological analysis and management. This is because most biota in fire-prone ecosystems are adapted to specific fire regimes (Keeley 1986; Bond and van Wilgen 1996) that when altered threaten their persistence (Franklin *et al.* 2016). Thus, it is important to account for the distinctive characteristics of wildfires that resulted in these species' adaptations.

In terms of projecting future fire regimes, there are a range of dynamic models available that simulate potential fire behaviour and vegetation patterns under changing environmental conditions, but many have drawbacks, and uncertainty is an ongoing concern (Keane *et al.* 2019). Fire regime ecoregion mapping could be an additional tool for framing interpretation of projections because of the focus on the multivariate drivers of fire regime change rather than the outcome of change (i.e. differences in fire patterns). Peters *et al.* (2004) provided a model for how to deal with the non-linearities in complex problems such as wildfire forecasting. One of the tricky problems involves expected fire-driven type conversions (e.g. Davis *et al.* 2019; Syphard *et al.* 2019) and thus, it may be necessary to account for expected changes in vegetation as drivers of fire regime changes (Syphard *et al.* 2018). Future fire ecoregion maps could be derived using mapped projections of vegetation or the other dynamic variables used here.

Conflicts of interest

The authors declare no conflicts of interest.

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References

Archibald S, Lehmann CER, Gómez-Dans JL, Bradstock RA (2013) Defining pyromes and global syndromes of fire regimes. *Proceedings of the National Academy of Sciences of the United States of America* **110**, 6442–6447. doi:10.1073/PNAS.1211466110

Bailey RG (1980) Description of the ecoregions of the United States. Misc. Publication 1931. US Department of Agriculture, Washington, DC.

Ball GH, Hall DJ (1965) 'ISODATA, a novel method of data analysis and pattern classification.' (Stanford Research Institute: Menlo Park, CA)

Barbour M, Keeler-Wolf T, Schoenherr AA (2007) 'Terrestrial vegetation of California.' (University of California Press: Oakland, CA)

Bond WJ, van Wilgen B (1996) 'Fire and plants.' (Chapman & Hall: London)

Bowman DM, Balch J, Artaxo P, Bond WJ, Cochrane MA, D'Antonio CM, DeFries R, Johnston FH, Keeley JE, Krawchuk MA, Kull CA, Mack M, Moritz MA, Pyne S, Roos CI, Scott AC, Sodhi NS, Swetnam TW (2011) The human dimension of fire regimes on Earth. *Journal of Biogeography* **38**, 2223–2236. doi:10.1111/J.1365-2699.2011.02595.X

Bradstock RA (2010) A biogeographic model of fire regimes in Australia: current and future implications. *Global Ecology and Biogeography* **19**, 145–158. doi:10.1111/J.1466-8238.2009.00512.X

Davis F, Borchert M (2006) Central Coast Bioregion. In 'Fire California's ecosystems' (Eds NG Sugihara, JW van Wagtendonk, K Shaffer, J Fites-Kaufman, AE Thode) pp. 321–329. (University of California Press: Oakland, CA)

Davis KT, Dobrowski SZ, Higuera PE, Holden ZA, Veblen TT, Rother MT, Parks SA, Sala A, Maneta MP (2019) Wildfires and climate change push low-elevation forests across a critical climate threshold for tree regeneration. *Proceedings of the National Academy of Sciences of the United States of America* **116**, 6193–6198. doi:10.1073/PNAS.1815107116

Falk DA, Miller C, McKenzie D, Black AE (2007) Cross-scale analysis of fire regimes. *Ecosystems* **10**, 809–823. doi:10.1007/S10021-007-9070-7

Franklin J, Serra-Diaz JM, Syphard AD, Regan HM (2016) Global change and terrestrial plant community dynamics. *Proceedings of the National Academy of Sciences of the United States of America* **113**, 3725–3734. doi:10.1073/PNAS.1519911113

Keane RE, Cary GJ, Parsons R (2003) Using simulation to map fire regimes: an evaluation of approaches, strategies, and limitations. *International Journal of Wildland Fire* **12**, 309–322.

Keane RE, Loehman RA, Holsinger LM (2019) Selecting a landscape model for natural resource management applications. *Current Landscape Ecology Reports* **4**, 31–40. doi:10.1007/S40823-019-00036-6

Keeley JE (1986) Resilience of Mediterranean shrub communities to fire. In 'Resilience in Mediterranean-type ecosystems'. (Eds B Dell, AJM Hopkins, BB Lamont) pp. 95–112. (Springer: Dordrecht, The Netherlands)

Keeley JE, Pausas JG (2019) Distinguishing disturbance from perturbations in fire-prone ecosystems. *International Journal of Wildland Fire* **28**, 282–287. doi:10.1071/WF18203

Keeley JE, Syphard AD (2017) Different historical fire-climate patterns in California. *International Journal of Wildland Fire* **26**, 253–268. doi:10.1071/WF16102

Littell JS, McKenzie D, Peterson DL, Westerling AL (2009) Climate and wildfire area burned in western U.S. ecoprovinces, 1916–2003. *Ecological Applications* **19**, 1003–1021. doi:10.1890/07-1183.1

Moreno MV, Conedera M, Chuvieco E, Pezzatti GB (2014) Fire regime changes and major driving forces in Spain from 1968 to 2010. *Environmental Science & Policy* **37**, 11–22. doi:10.1016/J.ENVSCI.2013.08.005

Morgan P, Hardy CC, Swetnam TW, Rollins MG, Long DG (2001) Mapping fire regimes across time and space: understanding coarse and fine-scale fire patterns. *International Journal of Wildland Fire* **10**, 329–342. doi:10.1071/WF01032

Omernik JM (1987) Ecoregions of the conterminous United States. *Annals of the Association of American Geographers* **77**, 118–125. doi:10.1111/J.1467-8306.1987.TB00149.X

Omernik JM, Griffith GE (2014) Ecoregions of the conterminous United States: evolution of a hierarchical spatial framework. *Environmental Management* **54**, 1249–1266. doi:10.1007/S00267-014-0364-1

Peters DPC, Pielke RA, Bestelmeyer BT, Allen CD, Munson-McGee S, Havstad KM (2004) Cross-scale interactions, nonlinearities, and forecasting catastrophic events. *Proceedings of the National Academy of Sciences of the United States of America* **101**, 15130–15135. doi:10.1073/PNAS.0403822101

Rollins MG (2009) LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire* **18**, 235–249. doi:10.1071/WF08088

Safford HD, Van de Water KM (2014) Using fire return interval departure (FRID) analysis to map spatial and temporal changes in fire frequency on national forest lands in California. USDA Forest Service, Pacific Southwest Research Station Research Paper PSW-RP-266. (Albany, CA, USA). doi:10.2737/PSW-RP-266

Syphard AD, Keeley JE (2016) Historical reconstructions of California wildfires vary by data source. *International Journal of Wildland Fire* **25**, 1221–1227. doi:10.1071/WF16050

Syphard AD, Keeley JE, Pfaff AH, Ferschweiler K (2017) Human presence diminishes the importance of climate in driving fire activity across the United States. *Proceedings of the National Academy of Sciences of the United States of America* **114**, 13750–13755. doi:10.1073/PNAS.1713885114

Syphard AD, Sheehan T, Rustigian-Romsos H, Ferschweiler K (2018) Mapping future fire probability under climate change: does vegetation matter? *PLoS One* **13**, e0201680. doi:10.1371/JOURNAL.PONE.0201680

Syphard AD, Brennan TJ, Keeley JE (2019) Drivers of chaparral type conversion to herbaceous vegetation in coastal Southern California. *Diversity & Distributions* **25**, 90–101. doi:10.1111/DDI.12827

Warren DL, Glor RE, Turelli M (2010) ENMTools: a toolbox for comparative studies of environmental niche models. *Ecography* **33**, 607–611. doi:10.1111/J.1600-0587.2009.06142.X

Wells ML, O'Leary JF, Franklin J, Michaelsen J, McKinsey DE (2004) Variations in a regional fire regime related to vegetation type in San Diego County, California. *Landscape Ecology* **19**, 139–152. doi:10.1023/B:LAND.0000021713.81489.A7

Whitlock C, Higuera PE, McWethy DB, Briles CE (2010) Paleoecological perspectives on fire ecology: revisiting the fire-regime concept. *The Open Ecology Journal* **3**, 6–23. doi:10.2174/1874213001003020006

Appendix 1. Mean values of biophysical and anthropogenic variables summarised after unsupervised classification of eight California fire regime ecoregions (variable descriptions provided in Table 1)

NDVI, normalised difference vegetation index

	Ecoregion number							
	1	2	3	4	5	6	7	8
Region size (million ha)	37.49	12.36	109.26	76.65	69.02	39.71	28.15	30.68
Elevation (m)	1619.36	1235.86	697.58	122.97	502.17	1197.45	2491.49	1020.8
Topographic heterogeneity (0–1)	0.17	0.81	0.16	0.05	0.43	0.52	0.72	0.9
Annual precipitation (mm)	566.06	235.01	157.61	416.77	727.38	1493.67	967.41	1177.96
Summer precipitation (mm)	12.42	7.77	6.35	2.07	3.33	14.37	12.69	9.48
Annual snowpack (mm)	127.66	1.15	0	0	0.04	157.32	531.37	56.81
Annual minimum temperature (°C)	−5.77	1.39	3.03	4.13	3.53	−0.7	−7.32	1
Annual maximum temperature (°C)	26.51	33.34	36.84	32.84	30.31	26.61	21.05	28.75
Actual evapotranspiration (mm)	258.76	175.23	144.42	319.72	380.78	448.38	258.55	388.45
Climatic water deficit (mm)	86.72	97.1	94.08	108.27	103.19	88.16	101	93.9
NDVI annual minimum(−1–1)	0.22	0.07	0.06	0.16	0.3	0.45	0.21	0.38
NDVI annual maximum(−1–1)	0.44	0.2	0.18	0.61	0.63	0.74	0.42	0.71
Housing density (units km^{-2})	1.39	2.02	7.85	126.23	9.94	0.45	0.03	0.41
Distance to roads (m)	658.84	2620.21	1331.52	270.87	557.36	470.33	4397.37	1202.57