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Trends and drivers of fire activity vary across California aridland ecosystems

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ABSTRACT

Fire activity has increased in western US aridland ecosystems due to increased human-caused ignitions and the expansion of flammable exotic grasses. Because many desert plants are not adapted to fire, increased fire activity may have long-lasting ecological impacts on native vegetation and the wildlife that depend on it. Given the heterogeneity across aridland ecosystems, it is important to understand how trends and drivers of fire vary, so management can be customized accordingly. We examined historical trends and quantified the relative importance of and interactions among multiple drivers of fire patterns across five aridland ecoregions in southeastern California from 1970 to 2010. Fire frequency increased across all ecoregions for the first couple decades, and declined or plateaued since the 1990s; but area burned continued to increase in some regions. The relative importance of anthropogenic and biophysical drivers varied across ecoregions, with both direct and indirect influences on fire. Anthropogenic variables were equally important as biophysical variables, but some contributed indirectly, presumably via their influence on annual grass distribution and abundance. Grass burned disproportionately more than other cover types, suggesting that addressing exotics may be the key to fire management and conservation in much of the area.

1. Introduction

Wildfire across western US desert and semiarid ecosystems has historically been rare, with fire spread limited by low fuel continuity within landscapes dominated by sparse shrubland and bare ground (Brooks et al., 2018). Nevertheless, fire regimes vary in aridland ecosystems because of their tremendous floristic diversity across large ecological gradients (Brooks and Matchett, 2006; Belnap et al., 2016). In recent decades, wildfire activity has increased across portions of western US aridland ecosystems (e.g., Balch et al., 2013; Dennison and Brewer, 2014). However, Brooks and Matchett (2006) found substantial variation in both fire frequency and area burned across different elevations and vegetation zones.

Altered fire regimes in arid ecosystems are important ecologically because many succulent and desert woody plant species are not adapted to fire (Brown and Minnich, 1986; Brooks and Chambers, 2011). Thus, increases in fire activity may produce long-lasting impacts on ecological structure and native plant community composition (Brooks, 2012). Large fires may also threaten animal populations either directly or via changes in vegetation structure required for habitat (Esque et al., 2003; Vamstad and Rotenberry, 2010; van Mantgem et al., 2015).

Changing fire patterns in arid lands are primarily associated with increased human-caused ignitions (Brooks and Esque, 2002; Brooks and Matchett, 2006) and the growth and expansion of exotic annual grasses, which provide highly flammable fine-fuel biomass and fuel continuity (Brooks, 1999; Brooks and Matchett, 2006; Zouhar et al., 2008; Balch et al., 2013; Brooks et al., 2018). Anthropogenic ignitions are strongly associated with proximity to human land use and disturbance (Syphard et al., 2008; Syphard and Keeley, 2015), although large fires tend to occur in more remote areas (Gray et al., 2014). Nevertheless, ongoing urban growth and recent expansion of energy infrastructure are likely altering fire pattern and frequency, especially because lightning ignition-

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efficiency is quite low in US western deserts (Abatzoglou et al., 2016). In addition, most of the rapidly growing urban areas are in the desert valleys and foothills where disturbance provides conduits for further spread and dispersal of the already-present invasive grasses (Brooks and Pyke, 2002). This mix of high ignition probabilities and disturbance is the perfect storm for invasive grass-driven wildfires.

In addition to providing corridors for invasion, humans may indirectly promote the growth and expansion of exotic grasses via dry nitrogen deposition. Nitrogen emissions are high in California due to vehicle emissions and agriculture (Fenn et al., 2010), and exotic annual grass responds favorably to increased nutrients in soils or via nitrogen release due to fire, much better than native perennial plants (Brooks and Pyke, 2002; Allen et al., 2009; Rao et al., 2009; Esque et al., 2010). Therefore, nitrogen deposition may be an important indirect driver of increased fire activity via its effect on biomass production.

Fire itself may also contribute to the spread of exotic grasses, resulting in a positive feedback effect referred to as the grass-fire cycle (D'Antonio and Vitousek, 1992; Esque et al., 2003; Keeley et al., 2012). The establishment of grasses increases landscape flammability and the likelihood of fire, which in turn creates disturbed conditions conducive for further grass establishment and growth (Brooks, 2012). Several studies have provided indirect evidence to suggest that such a grass-fire cycle is developing across portions of western US aridland ecosystems (Schmid and Rogers, 1988; Brown and Minnich, 1986; Brooks and Matchett, 2006; Balch et al., 2013).

Given the complexity of factors driving increased fire activity in aridland ecosystems, a number of studies have focused on identifying the most important drivers, primarily biophysical factors such as herbaceous biomass production, climate, and terrain variables (e.g., Brooks and Matchett, 2006; Hegeman et al., 2014; Gray et al., 2014; Tagestad et al., 2016). Results of this work have shown that fire dynamics are strongly mediated by seasonal precipitation patterns and interannual moisture variability. Fewer studies have quantified the relative role of anthropogenic factors, although road density was explored in Gray et al. (2014) and Brooks and Esque (2002). However, given the role of humans in influencing both fire ignitions and the distribution of exotic annuals, the pattern and extent of human land use, and indirect human factors such as nitrogen deposition, likely influence fire patterns.

Despite a general understanding that trends and drivers of fire activity vary geographically across aridland ecosystems (e.g., Brooks et al., 2018), more systematic study is needed to understand how the spatiotemporal factors that influence fire activity vary across different ecoregions, and how these factors have contributed to changes in fire activity in recent decades. In addition to projected changes in climate, changes in land use across southeastern California are highly probably, particularly given that it is a highly desirable area for the development of renewable energy. For regional conservation planning, therefore, it is important to understand why and where invasive-driven wildfires are occurring. This information is critical for identifying and prioritizing the location and timing of management and restoration approaches in different geographical areas.

Our first objective was to examine historical trends in fire activity across five major arid and semi-arid ecoregions from 1970 to 2010 spanning the majority of southeastern California and query how these trends vary by land cover type. Secondly, we sought to quantify the relative importance of multiple human and biophysical factors in driving patterns of fire activity across the different ecoregions. Finally, we evaluated how large fires are structured by factors such as exotic grass cover and different land uses.

1.1. Research questions

1) Have fire frequency and area burned changed in the last several decades and have these trends varied by vegetation cover type or ecoregion?
2) Has there been a disproportionately large proportion of exotic grassland burning compared to other vegetation cover types?
3) What are the most important human and biophysical factors explaining fire occurrence and large fire occurrence in different ecoregions?
4) How do the drivers of large fire activity interact, particularly relative to exotic grass and land use?

To answer our questions, we first assembled an extensive spatial database of historical fire occurrence and a range of potential biophysical and anthropogenic explanatory variables. After assessing historical trends in fires and large fires among ecosystem and vegetation types, we developed statistical hierarchical partitioning models to quantify the relative importance of explanatory variables. Finally, to explore interactions among direct and indirect drivers of grass and fire activity, we developed structural equation models for the different ecoregions.

2. Methods

2.1. Study area and ecoregions

The study area encompassed all the land area within the Desert Renewable Energy Conservation Plan (DRECP) Boundary in addition to a 12 km buffer surrounding this area, together comprising nearly 2.5 million ha (Fig. 1). The DRECP boundary was developed to serve as an analysis area for statewide renewable energy planning efforts in which the objective is to facilitate development of energy infrastructure while protecting plant and wildlife communities (www.drecp.org, accessed 5/8/16).

To capture the inherent variation in human and biophysical characteristics across this large region, we used Omernik's Level III Ecoregions of the Conterminous United States (Omernik, 1987) to stratify the study area into five broad regions, including the Central Basin and Range (“Central Basin”), Mojave Basin and Range (“Mojave”), Sierra Nevada, Southern California Mountains (“SoCal Mts”), and Sonoran Basin and Range (“Sonoran”). A small portion of the Southern California/Northern Baja Coast ecoregion occurred within the study area, which we lumped with the Sonoran Basin ecoregion; we also merged small portions of the Central California Valley and Central California Foothills and Coastal Mountains with the Sierra Nevada ecoregion. The Omernik ecoregions were compiled based upon spatial differentiation of biotic and abiotic factors, such as geology, vegetation, climate, and land use, that affect or reflect ecosystem integrity and quality. Because only portions of some ecoregions fall within the DRECP boundary, these areas will reflect characteristics of arid or semi-arid lands within those ecoregions, but characteristics of entire ecoregion areas may not be represented.

2.2. Fire data and trend analysis

To explore trends across as long a time period as possible, we assembled a historical database that included the spatial coordinates and area burned for all fires on Federally owned lands from 1970 to 2010. These data included fire occurrence information from lands owned or managed by the National Park Service, the Bureau of Indian Affairs, the Bureau of Land Management, the U.S. Fish & Wildlife Service (USFWS), and the U.S. Forest Service. Data were downloaded from Wildland Fire Management Information (https://www.nifc.blm.gov/cgi/WfmiHome.cgi, accessed 11/30/16) for Department of Interior agencies and included information from individual fire reports. Information on USFS fires was obtained from the National Wildfire Coordinating Group at http://fam.nwcg.gov/fam-web/weatherfirecd/state_data.htm, accessed 11/30/16). We deleted DOI fires categorized as "Assist Fires," which represent support actions by Federal agencies. We also deleted all fires with a size of 0 acres. Each fire listed in this database contained information on its date and size. Thus, we delimited large fires to be those equal to or larger than 20 ha, which is the size assumed to best separate fires according to annual fuel loads that are sufficient for significant spread (Gray et al., 2014).

Using this historical spatial dataset, we conducted simple map overlays to separate the fires into the ecoregion they occurred in as well as their general vegetation cover type (details on vegetation below). Because these data were only available as point locations, it is possible that large fires could have crossed into another ecoregion or vegetation type, but we could not assess that. For these ecoregions and cover types, we then plotted the data over time and calculated simple linear and quadratic trend models to determine if there were any significant changes in number of all or large fires, or area burned, over time. We explored quadratic functions for all models, but only plotted the quadratic term when it was significant.

For statistical analyses that did not depend upon consistent reporting over time, we supplemented the Federal fire database with more contemporary data for fires on non-Federal lands. These data were available from 1992 to 2013 from the National Interagency Fire Program Analysis, Fire-Occurrence Database (FPA FOD) (Short, 2014), which also included spatial coordinate information and area burned for each fire. However, these fires represent a small fraction of the fire activity in the study area, as 68% of all fires and 97% of area burned during this period occurred on Federal lands.

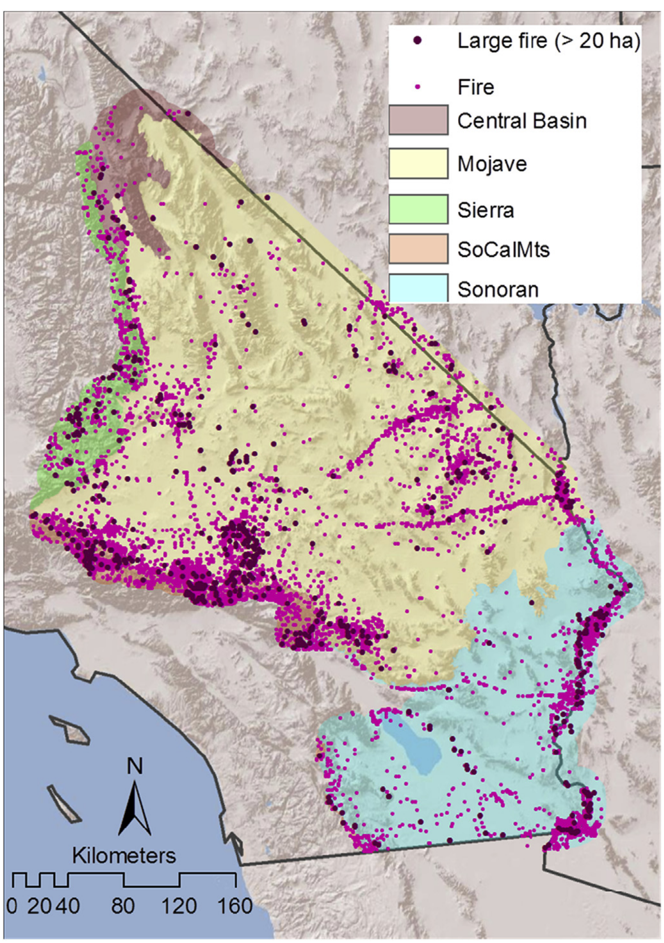

Fig. 1. Fire occurrence locations in the five ecoregions of the Desert Renewable Energy Conservation Plan (DRECP) study area.

2.3. Vegetation and NDVI data

To analyze fire activity trends among different vegetation types, we delineated vegetation cover primarily according to the 2008 LANDFIRE Existing Vegetation Type Layer map (LANDFIRE, 2008), as this product has been useful in analyzing fire patterns in previous work (Brooks et al., 2018). The LANDFIRE data are mapped at 30-m resolution based on a combination of decision tree models, field data, Landsat 7 imagery from 2001, elevation, and biophysical gradient data. Using the life form classification (National Vegetation Classification System Physiognomic Class), we extracted historical mapped fire data for these life-form types: grass, scrub shrub, tree-dominated, sparsely vegetated, and non-vegetated. Although some vegetation changes may have occurred, we assumed no major changes in life form type during the course of our analysis. For trend analysis, however, we focused on the three life forms where the majority of fires occurred: grass; scrub shrub, and tree-dominated. We additionally created a binary map of grass or no grass, i.e., areas mapped as primarily grassland, from these data to use as a predictor variable in the statistical analysis of fire drivers.

We added a riparian cover class to our map through an overlay with the Land Cover/Natural Vegetation Communities map, a 30-m resolution raster layer produced by the California Department of Fish and Game Vegetation Classification and Mapping Program and contractor Aerial Information Systems (Menke et al., 2013). This map was developed through airphoto interpretation of 2010 1-m National Agricultural Imagery Program imagery. Although most of the map has a minimum mapping unit (MMU) of 4.05 ha, wetlands and wash types were mapped at 0.405 ha MMU. Therefore, we overlaid the two maps and converted any class that was wetland, wash, or riparian in the Land Cover/Natural Vegetation Communities map into a "riparian" class for our own map.

Although the static map of grass from the LANDFIRE map delineates areas with permanent herbaceous cover, the biomass of annual grasses across the landscape varies from year to year depending on climatic factors such as precipitation (e.g., Bradley and Mustard, 2006). Studies have shown strong antecedent relationships between precipitation and wildfire activity in herbaceous fuel-driven systems of the western US (e.g., Keeley and Syphard, 2015; Brooks et al., 2018). However, precipitation or drought indices represent an indirect estimate of fuel accumulation whereas remotely sensed landscape measures of vegetation productivity provide a potentially more direct link. Previous studies have shown that annual maps of the Normalized Difference Vegetation Index (NDVI) are useful for detecting annual variation in biomass and fine fuel production, and that annual maximum NDVI in particular is significantly related to large fire activity in the Sonoran (Gray et al., 2014) and Mojave (Hegeman et al., 2014) deserts. The maximum NDVI in the year before a fire has also been significantly positively associated with fire activity because it may be indicative of biomass available for burning in the current year (Gray et al., 2014).

We calculated the maximum annual NDVI for years 1984–2010 using USGS Landsat imagery (http://landsat.usgs.gov/Landsat_Search_and_Download.php, accessed 6/2/16). We used the 8-day composite surface reflectance product from Landsat missions 4, 5 and 7 at 30-m spatial resolution that attempts to correct for atmospheric affects. Maximum NDVI was calculated from all available 8-day composites within a calendar year that were not biased by cloud cover.

In addition to maps of fine fuel variability, the standard deviation of NDVI within a dry season has been useful for mapping the distribution and heterogeneity of perennial vegetation in desert ecosystems (Gray et al., 2014). This is because fine-fuel biomass of exotic annuals should be lowest in the driest year. Therefore, to create one map representing long-term perennial vegetation, we divided the annual maximum NDVI map for 1990, the driest year in our record, into categories reflecting up to four standard deviations from the mean in both positive and negative directions.

2.4. Climatic water deficit

Climatic water deficit (CWD) is an integrative measure of drought stress that has been strongly associated with vegetation distribution in California (e.g., McIntyre et al., 2015; McCullough et al., 2015) and at much larger scales (Stephenson, 1998). Calculated as the difference between potential and actual evapotranspiration, CWD accounts for a suite of climatic and edaphic factors, including precipitation, temperature, relative humidity, radiation, and soil-water holding capacity, and vegetative cover. Because of the integrative nature of this variable, we used it to represent potential climatic influences on fire patterns. We acquired annual water-year accumulated CWD at 270-m resolution produced by the Basin Characterization Model (BCM) (Flint and Flint, 2007) to relate yearly fire activity to annual CWD. In addition, we used a 30-year (1971–2000) statistical summary of CWD as a predictor because we assumed this variable would provide the best spatial representation of long-term moisture gradients across the landscape.

2.5. Terrain variables

To minimize the number of explanatory variables in our analysis, we only considered two terrain-related predictors. Elevation is strongly correlated with both fuel and fire patterns in California deserts (Brooks et al., 2018), so we used mosaicked map data from multiple 30m digital elevation models (DEMs) produced by the U.S. Geological Survey. We also used mapped data on terrain ruggedness produced by the Vector Ruggedness Measure for the study area. Calculated from a digital elevation model, this ruggedness measure captures the variation in the three-dimensional orientation of grid cells within a neighborhood, and this metric has been shown to effectively integrate variability in both slope and aspect (Sappington et al., 2007).

2.6. Anthropogenic variables

Because we were interested in the relative effect of different anthropogenic land use factors on patterns of fire activity, we developed separate maps of five anthropogenic variables to compare in a separate analysis. Three of these variables, including distance to minor roads, major roads, and urban development, have been important in explaining patterns of fire activity in other regions of California (Syphard et al., 2007, 2008). We used the 2000 Topographically Integrated Geographic Encoding and Referencing System TIGER/Line files from the U.S. Census to map minor roads in the region. For major roads, we used data developed by Geographic Data Technology, Inc. that delineated major thoroughfares, including interstate, U.S., and state highways, at a scale of 1:100,000 across the study area for the year 2002. To map the development footprint, we used decadal housing density data from a national data product (Hammer et al., 2004), and thresholded these data into binary maps in which urban was defined as at least 128 units/km^2 (after Syphard et al., 2011a). For all of these vector maps, we created interpolated Euclidean distance grids covering the entire study area so we could relate their proximity to fire occurrence locations.

Because energy development is substantially more pervasive in the semiarid and desert portions of the state, we also explored the potential for fire patterns to be related to this kind of infrastructure. Using data on locations of point energy sources (including locations of oil and gas wells, wind turbines, and power plants), as well as powerline locations (https://www.sciencebase.gov/catalog/item/537f6c28e4b021317a871fc2, accessed 6/2/16), we developed two additional Euclidean distance grids to use as anthropogenic land use predictor variables.

Although we evaluated the relative importance of the above variables in a separate analysis, we used a composite variable representing the combined impact of anthropogenic land use and disturbance on the natural landscape to compare with the biophysical variables. This variable, terrestrial intactness, was developed using a fuzzy logic model that integrates measures of natural vegetation fragmentation with multiple measurements of landscape development, including the variables described above, into a single index (https://drecp.databasin.org/datasets/958719f2359e40b99ca683d1a473ba8d). The result is continuous map ranging from −1 to 1 in which high intactness represents areas with connected, high-quality native vegetation and low intactness represents areas that are highly fragmented and disturbed.

In addition to land use variables, we also investigated the potential effect of nitrogen deposition patterns on fire activity. For this variable, we used a map of total annual deposition of reduced and oxidized nitrogen (kilograms of nitrogen per hectare per year), produced for California for 2002. Simulated N deposition was calculated for the most polluted two-thirds of the state on a 4-km resolution grid (Tonnesen et al., 2007), with the remaining areas modeled and mapped at 36 km. Approximately two-thirds of the western part of the DRECP study area fell within the most polluted two-thirds of the state.

2.7. Dataset assembly for statistical analysis

For all of the mapped predictor variables, we resampled the data to 30-m resolution, which was the finest of all datasets, and clipped them to the same extent. Resampling coarser-scale data to a finer resolution results in no loss of data, although there is potential for differentially representing spatial variance in the data distribution. We then extracted values from these mapped predictors at the locations of the fire occurrence data. Based on availability of NDVI data, a full dataset with at least a current and lag year restricted our analyses to fire occurrences during the years 1985–2011.

For statistical modeling, we also generated a random sample of background points across the study area to assess the effect of the predictor variables on patterns of fire activity relative to the variables' distribution across the rest of the landscape. Because the objective here was to understand the different drivers of fire activity, the effect of random sample number (i.e., prevalence of the dependent variable) was not as much a concern as it would be for prediction (Shmueli, 2010). Nevertheless, the predictive accuracy of regression modeling has been shown to improve when using a large number of pseudo-absences equally weighted to the presences for species distribution models (Barbet-Massin et al., 2012). Therefore, because we were developing separate models for each ecoregion, we developed a stratified random sampling design so that, for each ecoregion, we generated a random sample of background points equally weighted to the number of fires by a factor of two.

To assign data from temporal explanatory variables (i.e., annual

NDVI and CWD and decadal distance to development) to the random background points, we used a weighting scheme based on the proportion of fires that occurred in each year. For example, if 10 percent of the fires occurred in 1991, we randomly assigned "1991" to 10 percent of the random background points and then extracted data for the explanatory variables corresponding to that year. Although we assigned temporal data to random background points across the entire study area, there was a strong spatiotemporal coherence in fire activity across the region. That is, big fire years were significantly and positively correlated among all ecoregions.

2.8. Hierarchical partitioning

Hierarchical partitioning is an effective method for quantifying the relative importance of a series of explanatory variables in a multiple-regression analysis (Chevan and Sutherland, 1991). In particular, the algorithm builds a hierarchy of regression models using all combinations of explanatory variables and then provides a measure of their independent and joint influences on the response. An independent contribution is that for which an explanatory variable is solely responsible, whereas the joint contribution is the effect of the variable given its joint effects with other variables. Thus, this approach also overcomes issues related to multicollinearity.

We developed hierarchical partitioning models for two sets of explanatory variables to investigate their relative influence on the distribution of all fires and of large fires in each ecoregion. The first set included the five land use explanatory variables. The second set included all static and dynamic spatial explanatory variables with terrestrial intactness substituted for the different land cover variables. We included both NDVI and the NDVI lag year along with current-year CWD in the hierarchical partitioning analysis. To minimize the number of explanatory variables, we did not include the prior-year CWD for hierarchical partitioning because we assumed it would primarily be reflected in the NDVI variables. We did consider the CWD lag year for structural equation modeling (below). We did not develop models for large fires in the Central Basin region because the sample size was too small. For all models, we specified logistic regression with family "binomial" and log likelihood as our goodness of fit measure. We developed the models using the hier.part package, version 1.0–4 in R (MacNally and Walsh, 2004; R Core Team., 2016). The sum of results for each variable equals the goodness of fit measure of the full model minus the goodness of fit measure of the null model.

2.9. Structural equation modeling

We used structural equation models to examine the interaction among variables explaining large fire occurrence, as those are most important ecologically. In particular, we hypothesized that variables shown to be important in explaining large fire distribution do not directly affect fire, but instead have an indirect effect via their influence on fuel conditions.

Structural equation models differ from regression modeling used in hierarchical partitioning in that they can assess whether a variable is indirectly affecting the outcome through its influence on a different variable. Structural equation models also differ from other statistical approaches because they test whether the data are consistent with a pre-determined hypothesis. Thus, a conceptual model is developed a priori (Grace and Pugesek, 1998), and the objective is to test whether the data are significantly different from this model.

We developed structural equation models for large fire occurrence in the four out of five DRECP ecoregions that had a large number of observations. We performed the modeling using Mplus version 5.1 (Muthén and Muthén, 1998–2011). Because the dependent variable in the analysis, large fire occurrence, was binary, we used the weighted least-squares estimator with mean and variance adjustment. To test whether the model fit the data, we evaluated chi-square and associated fit indices including RMSE of approximation and weighted root mean square residual (Hooper et al., 2008). For each ecoregion, we developed a full initial conceptual model based on our understanding of the factors that directly influence fire versus those whose influence is mediated by annual fluctuations in herbaceous fuel. We also considered the hierarchical partitioning results and correlations among predictor variables in the development of our initial conceptual models. For each region, we removed one path at a time from our initial model until we identified the best fit with the data.

Because of the dynamic nature of grasses and precipitation anomalies in driving large-fire activity, we developed and explored three indices to represent grass cover as a dependent variable. For the first two indices, we multiplied either current-year or past-year NDVI with the binary, static grass of map derived from the LANDFIRE vegetation map. Grass areas in the binary map were classified as 2, and non-grass as 1; thus, NDVI values were doubled in areas mapped as grass and unchanged otherwise. The third index multiplied the sum of both years of NDVI by the grass map. If this third index was the one that most significantly affected fire activity in a particular region, we also explored an index of climatic water deficit that summarized current and prior years.

3. Results

The five ecoregions captured the wide variation in biophysical and anthropogenic characteristics of the study area. The two lowest elevation ecoregions, Mojave and Sonoran Deserts were also the two driest (Table 1), but they differed substantially in vegetative cover (Fig. 2), with the Mojave having larger proportions of sparse and scrub shrub vegetation and the Sonoran having more non-vegetated and riparian areas. The Sierra Nevada and SoCal Mts regions had the highest fire density (although the SoCal Mts far exceeded the Sierra Nevada), nitrogen deposition, and tree cover, but the SoCal Mts are also heavily fragmented with the largest proportion of grass cover.

The Central Basin is similar to the Sierra Nevada and SoCal Mts in terms of elevation, but this region has the lowest fire density and highest terrestrial intactness, with low anthropogenic influence.

3.1. Trend analysis

Number of fires, number of large fires and area burned were the three fire variables used for ecoregion comparisons (Fig. 3). Except for the Central Basin ecoregion (Fig. 3a), there were significant trends for at least two variables for the rest of the ecoregions on Federal lands from 1970 to 2010. In all regions except for the SoCal Mts (Fig. 3d), the number of fires increased significantly from 1970 to the middle of the 1990s. Moreover, a relative absence of fire was seen in the Mojave and Sonoran ecoregions during the 1970s. There was a significant subsequent decline in the Mojave from 1990 to 2010 (Fig. 3b), but the trend reflected more of a plateau for the Central Basin, Sierra Nevada, and Sonoran (Fig. 3a,c,e). A similar nonlinear trend, with a step change, in large fires and area burned also occurred in the Mojave (Fig. 3b); but there was an increase over the 40-year period for large fires and area burned in the Sierra Nevada, SoCal Mts, and the Sonoran, with a step change in area burned in the Sonoran.

For the three most flammable vegetation types (Fig. 4), all three fire variables showed a nonlinear trend of significant increase until the 1990s or 2000s, with not much change over the last 15 years.

The only exception was large grass fires which showed a significant increase in frequency from 1970 to 2010 (Fig. 4 a).

Relative to its area on the landscape, grass cover burned substantially more than other vegetation types, with approximately 18% of the class, based on cover classes extracted from all points, burning within the period (Fig. 5). The only other class that burned disproportionately more than its area of the landscape was tree cover, with approximately 9% burning in the same period. Although scrub shrub by far occupied the majority of the study area, only a very small proportion of it burned during the study period.

3.2. Hierarchical partitioning analysis

The relative independent contribution of anthropogenic variables to the distribution of all and large fires, showed differences among ecoregions (Fig. 6 a–b).

Overall, distance to all or major roads were more important for explaining all fires than large fires, although major roads were more important than all roads in the Sonoran and Mojave regions; and all roads were more important in the other three regions. All roads were consistently more important than major roads in the large-fire models; but road variables were relatively unimportant in the Mojave, and major roads were relatively unimportant in the Sonoran. In the Sonoran, distance to development was the strongest predictor of all fires and large fires, but this variable was not very important in the other large-fire models or in the all-fire models for the Mojave and Sierra Nevada. Proximity to energy development (either point energy sources or powerlines) was most important in the Mojave and Central Basin regions, although there were not enough data to plot large fires in the Central Basin.

When the anthropogenic variables were subsumed into terrestrial intactness for hierarchical partitioning of the larger set of predictor variables, terrestrial intactness was by far the most important variable explaining the distribution of all fires (Fig. 7a).

Nitrogen deposition was the second most important variable for the Mojave, Sierra Nevada, and SoCal Mtns, but did not contribute much in the Central Basin or Sonoran region. The relative contribution of the rest of the variables again varied markedly among ecoregions. This variation among ecoregions was even more pronounced when explaining the distribution of large fires (Fig. 7b). Aside from elevation and current-year climatic water deficit, which were among the most important variables in the Sierra and SoCal Mtns, no other variable was consistently important among ecoregions.

3.3. Structural equation modeling

The structural equation models that best fit the data in the two desert ecoregions, the Mojave (Fig. 8a) and the Sonoran (Fig. 8b) showed widely different dynamics driving fire activity. In the Mojave, large fires were positively influenced by grass and elevation, and they occurred in close proximity to powerlines. The best grass index for this model was NDVI from the prior year multiplied by the grass map, which in turn was positively influenced by nitrogen and the measure of perennial vegetation (standard deviation of dry-year NDVI). The negative influence of annual water stress indicated that wet years prior to the fire increased biomass production; however, grass was also associated with places on the landscape that, on average, experienced higher levels of water stress. Grass was also negatively influenced by terrestrial intactness.

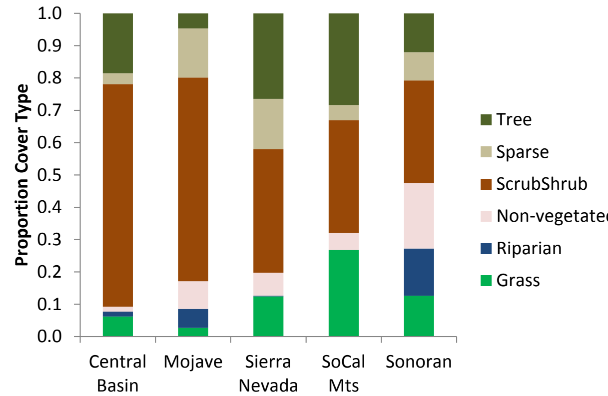

Fig. 2. Proportion of land cover type within the five ecoregions of the study area.

In the Sonoran Desert, as in the Mojave, large fires occurred within close proximity to anthropogenic land use, although instead of powerlines, here large fires occurred closer to roads or urban development. Unlike the Mojave, the grass index in the Sonoran Desert negatively influenced the occurrence of large fires, and instead large fires were positively influenced by the measure of perennial vegetation. Large fires here were both directly and indirectly, and negatively, affected by annual water stress. The best grass index in the Sonoran Desert was the one with both current and prior years of NDVI multiplied by the grass map, and this index was positively influenced by nitrogen and the measure of perennial vegetation, and negatively influenced by elevation and water stress.

The structural equation models for the two more semi-arid ecoregions, the Sierra Nevada (Fig. 9a) and the southern CA Mountains (Fig. 9b) were almost identical to one another and had more in common with the model for the Mojave than with the model for the Sonoran. Like the Mojave, the grass index positively influenced the occurrence of large fires. Large fires were also directly and positively associated with annual water stress and occurred close to roads. Also like the Mojave, grass was positively influenced by nitrogen and the measure of perennial vegetation, but in both of these regions, grass was also significantly associated with lower elevations. The positive influence of long-term water

Table 1
Summary statistics of key biophysical and anthropogenic attributes within the five ecoregions of the DRECP study area.

	Area (thousand ha)	Elevation (m)	Mean thirty-year (1981–2010) climatic water deficit (mm/yr)	Nitrogen deposition (kg/ha/yr)	Terrestrial intactness (−1 −1)	Fire Density (#/thousand ha)
Central Basin	467	1846	928	0.62	0.25	0.11
Mojave	788	897	1313	3.81	0.20	0.32
Sierra Nevada	570	1803	874	4.47	0.13	0.55
SoCal Mts	408	1466	931	7.78	−0.11	3.15
Sonoran	301	265	1337	3.80	0.01	0.31

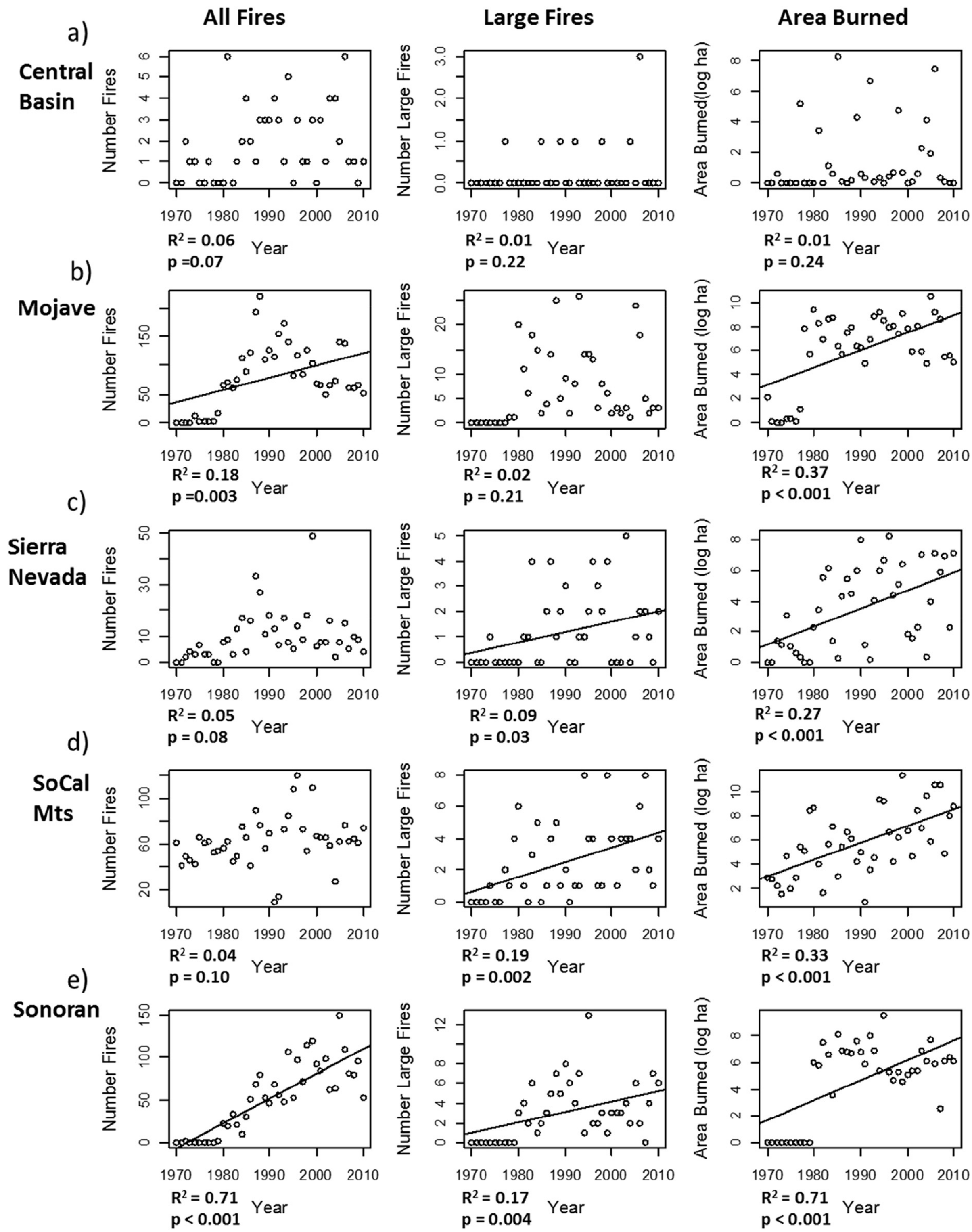

Fig. 3. Trends in all fires, large fires, and area burned for the five ecoregions comprising the Desert Renewable Energy Conservation Plan (DRECP) study region in California.

stress on annual grass was the only difference between the Sierra Nevada and the southern CA Mountains.

4. Discussion

As observed in other studies (e.g., Schmid and Rogers, 1988; Balch et al., 2013; Dennison and Brewer, 2014), fire activity has increased significantly across California aridland ecosystems over the last 40 years. However, this trend has not been geographically uniform, particularly in terms of number of fires, which have declined across much of the study area. A similar decline was reported in Brooks and Matchett (2006), which they attributed to a reduction in human-caused ignitions. Recent decreases in fire frequency have been reported across the entire state of California

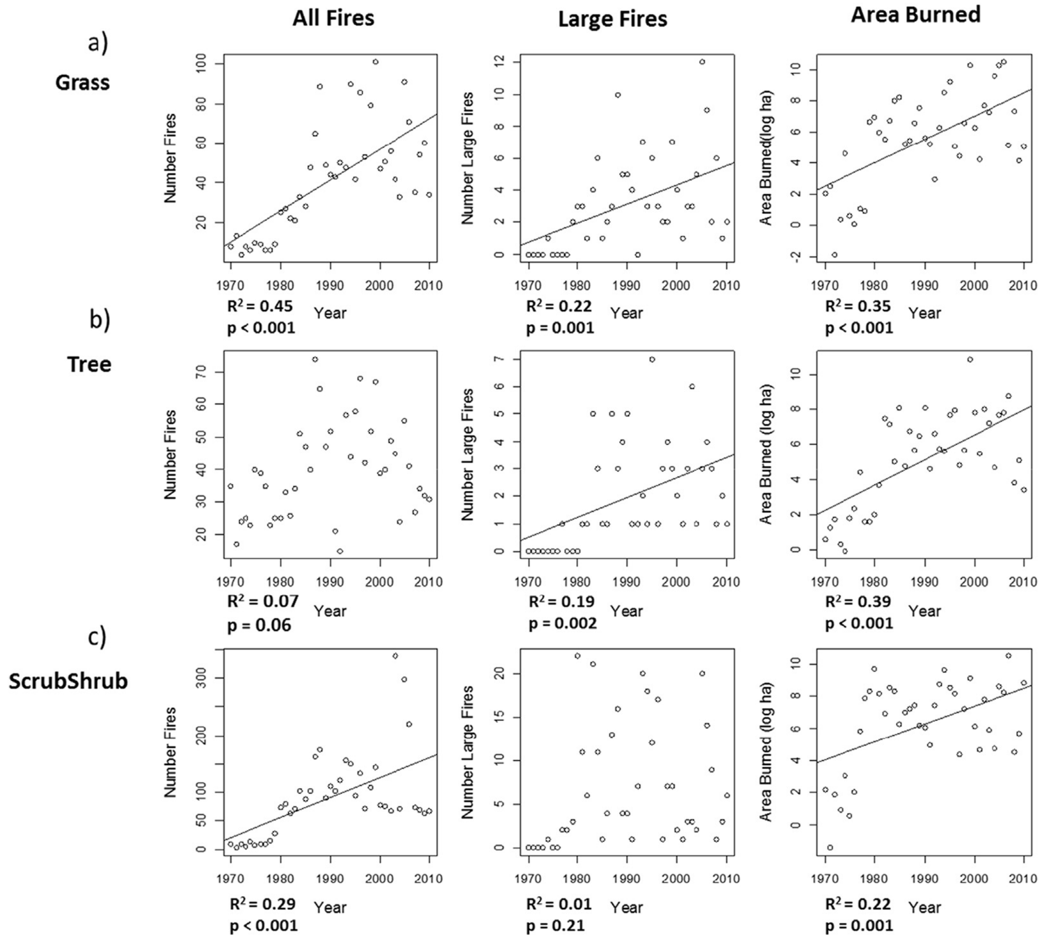

Fig. 4. Trends in all fires, large fires, and area burned for grass, tree, and scrub shrub vegetation cover classes in the Desert Renewable Energy Conservation Plan (DRECP) study region in California.

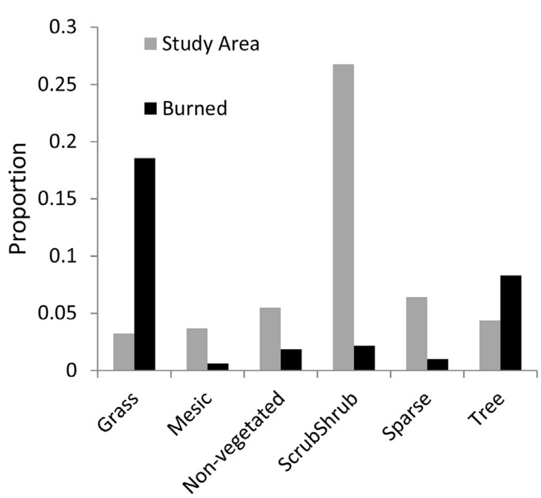

Fig. 5. Proportion of cover class in the study area and proportion of cover class burned by fire at least once from 1970 to 2010 in the Desert Renewable Energy Conservation Plan (DRECP) study region.

(Syphard et al., 2007; Keeley and Syphard, 2015), but the reasons for this decline remain unknown and are likely complex due to decline in some combination of the multiple causes of human-ignited fires (Syphard and Keeley, 2015). Another possibility is that the decline is due to the substantial increase in area burned, which reduces the potential for fire starts since fires do not generally start in recently burned landscapes due to fuel limitations. However, such leveraging effects (e.g. Price et al., 2012) are generally seen where a much greater proportion of the landscape burns each year than observed in this study (Fig. 5).

The continued increase in large fires and area burned in the Sierra Nevada, SoCal Mts, and Sonoran ecoregions nevertheless suggest that the decline in number of fires may not be related to climatic or fuel conditions that drive big fires. Although trends in 1970–2010 area burned for the Mojave differed from those reported by Brooks and Matchett (2006) (for the time period 1980–2004), we do show a similar decline in fire numbers. In an earlier study, Brooks and Esque (2002) attributed increased trends in fire frequency in desert ecosystems to a growing incidence of human-caused fires; but also reported that most large fires occurred in remote areas due to lightning. Abatzoglou et al. (2016) found that lightning-ignitions accounted for 58% of the area burned but only 13% of number of fires in the American Semi-Desert and Desert Ecoprovince that encompasses much of DRECP as well as southern Nevada and southern Arizona. The results here are consistent by showing that, while total number of fires was predominantly explained by human disturbance (low terrestrial intactness), large fires were explained by a more evenly distributed, and varied, range of human and biophysical factors in which no one factor in isolation was especially predictive.

Recent declines in fire frequency in the Mojave ecoregion may

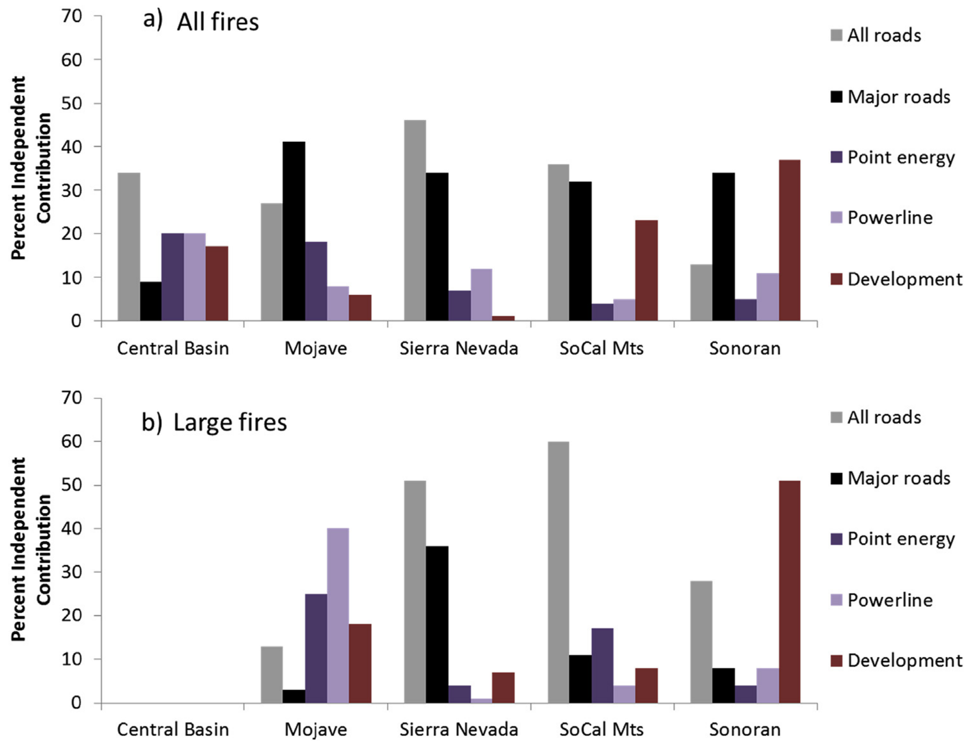

Fig. 6. Relative importance of five anthropogenic variables for influencing the spatial and temporal distribution of a) all and b) large fires across the Desert Renewable Energy Conservation Plan (DRECP) study area. Variable importance is measured as percent independent contribution in hierarchical partitioning multiple-regression models and does not represent direction of influence.

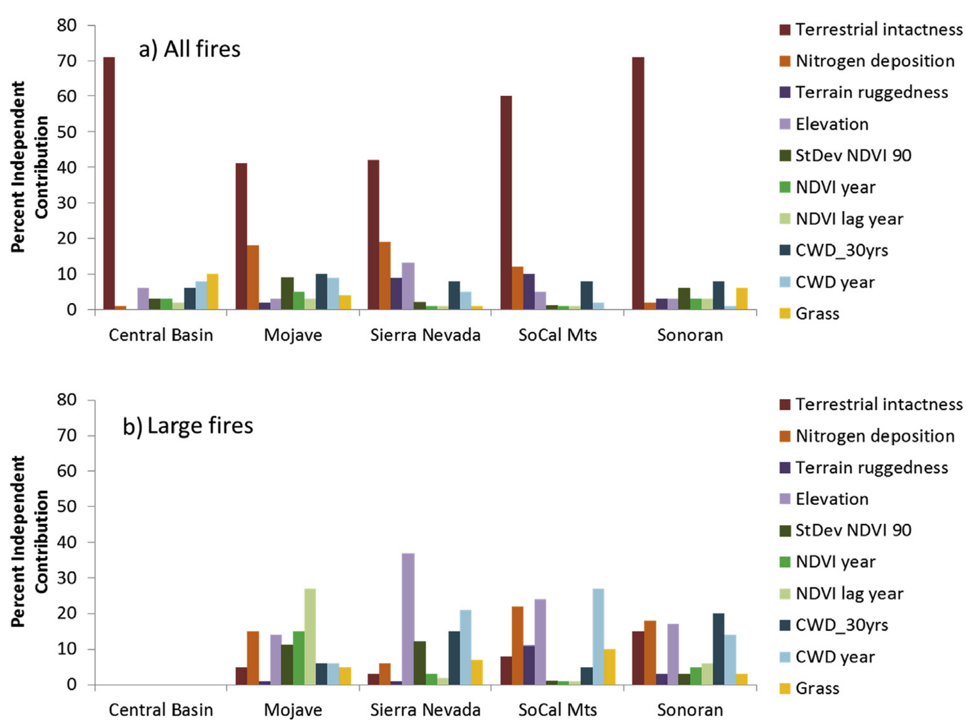

Fig. 7. Relative importance of human and biophysical variables for influencing the spatial and temporal distribution of a) all and b) large fires across the Desert Renewable Energy Conservation Plan (DRECP) study area. Variable importance is measured as percent independent contribution in hierarchical partitioning multiple-regression models and does not represent direction of influence.

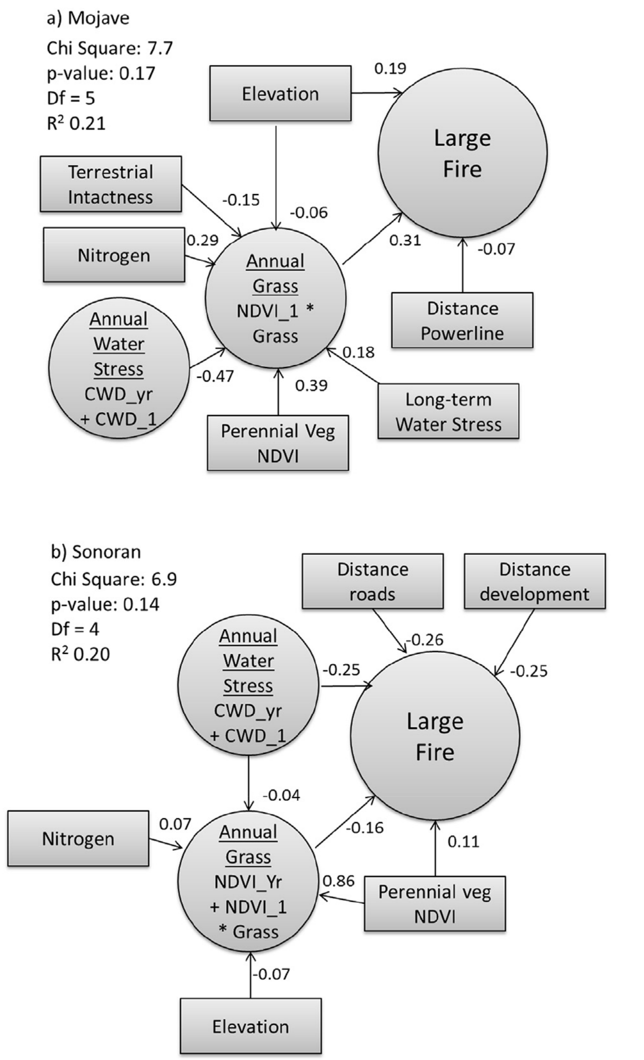

Fig. 8. Structural equation models for the a) Mojave and b) Sonoran Desert ecoregions that directly and indirectly explain the occurrence of large (>= 20 ha) fires. Circles represent either endogenous (dependent) variables or index variables, and squares represent exogenous (independent) variables. Arrows represent direction of effect and numbers beside the arrows are standardized coefficients, which indicate strength and direction of relationship. Non-significant p-values indicate data are not significantly different than the model, and the R^2 represents the total variability explained for the endogenous variable large fire.

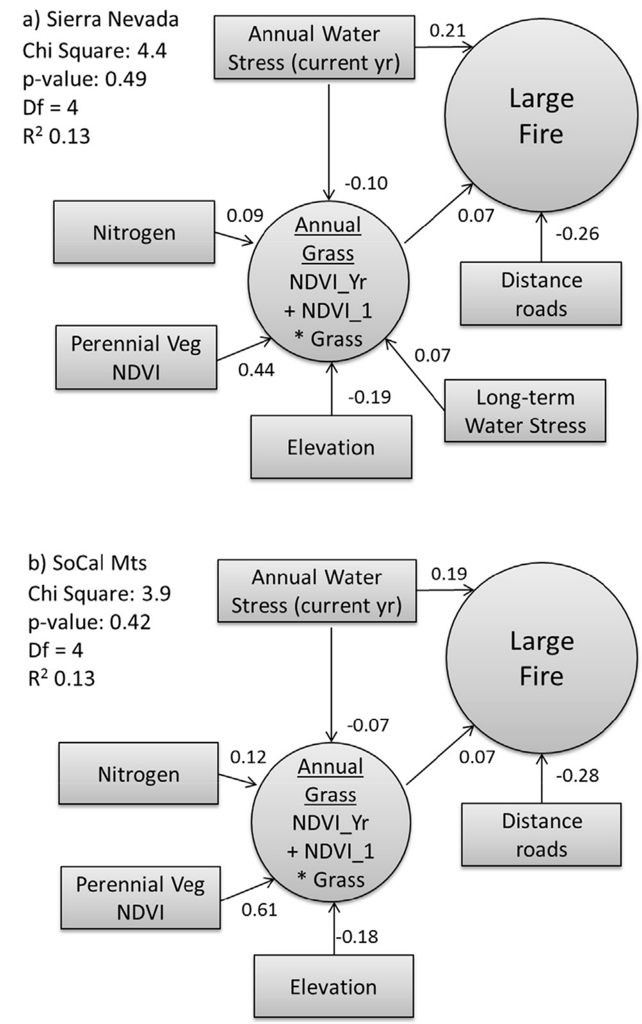

Fig. 9. Structural equation models for the a) Sierra Nevada and b) Southern CA Mountains semi-arid ecoregions that directly and indirectly explain the occurrence of large (> = 20 ha) fires. Circles represent either endogenous (dependent) variables or index variables, and squares represent exogenous (independent) variables. Arrows represent direction of effect and numbers beside the arrows are standardized coefficients, which indicate strength and direction of relationship. Non-significant p-values indicate data are not significantly different than the model, and the R^2 represents the total variability explained for the endogenous variable large fire.

also be linked to the persistent drought across much of the southwestern United States since the turn of the millennium, potentially associated with decadal variability such as the Pacific Decadal Oscillation (PDO) internal to the climate system (Dong and Dai, 2015). With the exception of the wettest water-year in more than 120 years across parts of the Mojave in 2005, nearly all water years from 2000 to 2016 had below-normal precipitation in contrast to a majority of years from 1980 to 1999 across the Mojave that had above-normal precipitation. Precipitation deficits and associated increases in CWD may limit the production of fine fuels and limit fire activity, whereas pluvial periods such as during the positive phase of the PDO during the 1980s and 1990s may have encouraged the growth of fine fuels and the expansion of exotic grasses (e.g., Salo, 2005).

Overall, none of the structural equation models resulted in high R^2 values, meaning that substantial uncertainty remains in terms of understanding large fire activity in these regions. Nevertheless, the relative variable importance and interrelationships among the drivers we studied provide new insights that can guide management and further study. For example, given the varying importance of different land use types across ecoregions, and the results from the structural equation models, this study shows that the role of humans in driving fire patterns has been important, variable, and complex; human influence extends beyond the direct ignition of fires. A clear example of that is the importance of nitrogen deposition in mediating large fire activity by promoting the growth of exotic annuals. The structural equation models illustrate this indirect relationship clearly, and this confirms other studies showing increased annual plant dominance as a result of high soil nutrient levels (Brooks, 1999), particularly in combination with high precipitation (Rao and Allen, 2010). Thus, human land use change and related nitrogen-producing activities, such as agriculture or energy production, as well as atmospheric movement of nitrogenous compounds from more coastal sites, are a growing concern (Galloway et al., 2004) due to their indirect effects on fire patterns, and direct effects on exotic grasses.

Of the five land use variables we explored in detail, none were consistently most important for all five regions except roads, which were uniformly important for total number of fires. The proximity of ignitions to roads in desert systems is consistent with other studies (e.g., Gray et al., 2014; Brooks and Esque, 2002). Roads were also directly related to large fires in the Sonoran, Sierra Nevada, and SoCal Mountains, likely because they serve as corridors where humans can start fires in remote parts of the landscape. Although roads were not directly related to large fires in the Mojave, terrestrial intactness, which accounts for roads, was an important anthropogenic effect on large fires through the indirect relationship with annual grass biomass.

In the Mojave, powerlines and other types of energy infrastructure (oil and gas wells, wind turbines, and power plants) were the most important anthropogenic land use contributors to large fires. Powerlines have been implicated for causing large, destructive fires in other parts of California, and in Australia (Cruz et al., 2012; Syphard and Keeley, 2015), in part because they may arc or fall, causing sparks, during high wind events, which are also conducive to extreme fire behavior. This anthropogenic ignition source could become even more problematic with continued infrastructure expansion, particularly in remote areas less accessible for fire suppression.

The large variation in relative importance of land use variables reflects differences in spatial patterning across the ecoregions, and this also highlights the importance of considering spatial context when evaluating ecological impacts of land use and fire disturbance (Syphard et al., 2013). For example, the Sonoran Desert had substantially different development patterns than the other ecoregions, with a larger proportion of non-vegetated land cover that included both developed and barren lands. Accordingly, distance to development was a more important influence there than in other regions. In addition to roads, the relationship between development and large fires in the Sonoran was direct in the structural equation model, meaning that proximity to development here was mostly related to human-caused ignitions rather than indirectly related to human disturbance of fuel patterns. The Sonoran region had low terrestrial intactness overall, so a spatial congruence between fragmented development patterns and flammable woody vegetation could explain how human ignitions close to developed areas resulted in large fires.

The Sonoran was the only region in which annual grass negatively influenced large fire occurrence, which may reflect its distribution relative to ignition sources. It is also possible that the extent of annual grass has not yet reached a threshold in which high rainfall years produce enough biomass continuity for substantial fire spread. On the other hand, the metric of woody perennial vegetation directly and positively influenced large fires in this region, and this could be due to large fires spreading through the well-connected and dense perennial vegetation associated with riparian or floodplain landscapes.

Although the metric of perennial vegetation is only a rough estimate of the distribution of long-lived or woody perennial species, it was helpful to separate this stable variable from the annual NDVI-based metrics associated with fluctuations of exotic grass biomass production. While perennial vegetation constitutes a portion of total primary production every year, keeping it separate in the modeling allowed the influence of woody versus annual fuels to be parsed out. Given the only significant influence of this variable in the other ecoregions was the positive contribution to interannual NDVI patterns, this suggests that woody vegetation was much less important than annual grass productivity in those regions. One potential limitation of this metric is that it might not be accurate at detecting potential for invasive herbaceous perennial vegetation, which could dry out or senesce in some dry years.

As with the trends in many of the ecoregions, the number of fires and area burned within the three cover types that we examined varied nonlinearly over time, with stronger recent declines in fire frequency than area burned. An important limitation of the study, however, is that with only point locations available, large fires may have burned across more than one cover type. Despite this limitation, the results showed that grass was the only cover type in which large fires significantly and linearly increased. Also, the recent trend in area burned is closer to a plateau rather than a decline as in the other two woody cover types. Finally, relative to its mapped area on the landscape, grass burned disproportionately more than all the cover types on the landscape. These results are consistent with other studies suggesting that, despite having lower fuel volume than the two woody vegetation types, grass is nevertheless more prone to burning in the desert, potentially due to its flammability and connectivity (e.g., Brooks, 1999; Zouhar et al., 2008; Brooks et al., 2018). Although it is difficult to directly measure a grass-fire cycle due to long-term data needs, these results provide strong indirect evidence for its potential, as in Balch et al. (2013).

The Mojave was the ecoregion in which large fire activity was most strongly associated with annual grass production, as the metric for grass was the most important direct factor contributing to large fires. Other studies have also suggested that the most vulnerable locations for establishment of a fire-grass cycle in California deserts are low to mid-elevation zones, particularly in the Mojave (Brooks and Matchett, 2006; Brooks et al., 2018). While the approach in those studies was to spatially stratify analyses of fire patterns and drivers by elevational zones, we used elevation as a predictor variable here to see its relative influence compared to other variables. Interestingly, elevation had a positive direct influence on fires in the Mojave, but it also had a negative indirect effect due to its association with annual grass biomass at lower elevations, although this effect was not very strong, as indicated by the low coefficient. The explanation for the direct link may be that lightning ignitions are likely to increase with elevation due with higher fuel density and lightning occurrence, and that fires occurring at higher elevations may become large due to their remoteness. Nevertheless, while lightning ignitions may occur more frequently in higher elevations, large fires may occur in lower elevations because of fuel or climatic patterns, or the presence of highways and roads.

In addition to the Mojave, annual grass biomass was a significant direct influence on large fires in both of the semi-arid mountainous ecoregions, the Sierra Nevada and the southern CA Mountains. In fact, the interrelationships between grass and fire were similarly structured in these two regions despite clear differences in mean fire density, nitrogen deposition, and terrestrial intactness. It could be that these were the two ecoregions located farthest west, where precipitation is higher; and, the majority of area burned occurred in areas where the two regions are adjacent. Although most of the studies on the relationship between fire and grass in western portions of California have been conducted in coastal chaparral and sage scrub (e.g., Lippitt et al., 2012; Keeley and Brennan, 2012), the results here suggest reason for concern for shrublands on the semi-arid eastern slopes of southern CA mountains as well. Positive feedbacks between fire and grass in woody shrublands presents a serious ecological threat due to the potential for widespread extirpation of native woody plant species that are not adapted to frequent fire (Bowman et al., 2014).

It is well established that exotic grass biomass fluctuates temporally in response to annual and seasonal patterns of precipitation, both in the fire year as well as the preceding year (e.g., Brooks and Berry, 2006; Gray et al., 2014; Hegeman et al., 2014), and that longer-term patterns of grass distribution may be related to multi-decadal variation in rainfall and its subsequent effect on fuel volume and moisture (Brooks et al., 2018). The structural equation modeling results confirm that annual patterns of climatic water deficit significantly influence biomass variation as measured by NDVI; and, in all regions except for the Mojave, annual water stress also directly influenced large fire occurrence, which could be related to fuel moisture conditions in other vegetation types that burned. This lack of direct relationship in the Mojave may be related to the strong effect of grass in mediating large fires in this region. The importance of long-term water stress, the average CWD over 30 years, reflects how longer-term fuel conditions vary over broad spatial gradients. Predictions of increased precipitation variability and other climatic factors suggest future conditions that may be even more conducive to increased annual grass distribution and abundance (Bradley, 2009; Abatzoglou and Kolden, 2011; Tagestad et al., 2016).

4.1. Conclusion and management considerations

In the vast aridland ecosystems of southeastern California, trends and drivers of fire not only vary geographically, but their interactions are complex and involve both human and biophysical factors. Although we identified clearly significant drivers of fire activity in each region, the low variance explained in the structural equation modeling also suggests there are additional unidentified factors at play. Thus, it will be important to consider the factors in management that directly influence fire as well as those that indirectly influence fire due to their effect on fuel distribution, quality, and abundance. Anthropogenic activities increase the occurrence of fire through ignitions, but also indirectly affect fire via the distribution and abundance of weedy herbaceous vegetation. Human-caused ignitions are also associated with different land use patterns that vary across the landscape. Thus, it is important to understand which land uses are most strongly contributing to human-caused fires in different regions and to customize ignition prevention or other management strategies accordingly.

Regardless of the source of ignition, the most limiting factor on large fires in arid ecosystems is fuel condition and continuity. Therefore, herbaceous and woody fuels management should be an obvious component in any fire management or conservation strategy. Fuels management in woody shrublands often implies ecological trade-offs (Driscoll et al., 2010), and desert ecosystems may be particularly sensitive to management activities that disturb and compact the soil (Webb, 2002). Therefore, fuels management in woody vegetation should be considered in light of its impact and effectiveness, which may be highest in strategic locations allowing firefighter access for suppression (Syphard et al., 2011b).

More important than fuels management of woody vegetation is the control of exotic grasses and other invasive species, like saltcedar (*Tamarix* spp.), which may impact riparian fire regimes (Brooks et al., 2018). Control can take the form of prescribed fire, livestock grazing, or herbicides, but these strategies should account for ecological context, with consideration of unintended ecological consequences (Brooks and Chambers, 2011). Although exotic grass abundance may decline during periods of low precipitation, high rainfall events can lead to quick recovery; thus, it is also important to consider how to prevent new invasions in places where exotic species have not already established. This should include identification and monitoring of potentially sensitive or vulnerable areas and developing customized, adaptable plants that account for invasion resistance and fire resilience of native species, as control is easiest in the early stages of invasion (Brooks and Berry, 2006; Brooks and Chambers, 2011). Of course, prevention considerations must also involve human land use and disturbance.

The results of this paper confirm that large fires fueled by invasive grasses are a general concern across most aridland ecosystems, but the nature of this relationship and interactions with other variables vary geographically. In addition to customizing fire and fuels management activities by region, hotspots of largest fire ignition and spread (Brooks et al., 2018) can also be modeled and mapped to identify those areas most in need of treatment or management (e.g., https://drecp.databasin.org/galleries/0c8c957534374db8bcb46d766fe1792c#expand=110631).

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