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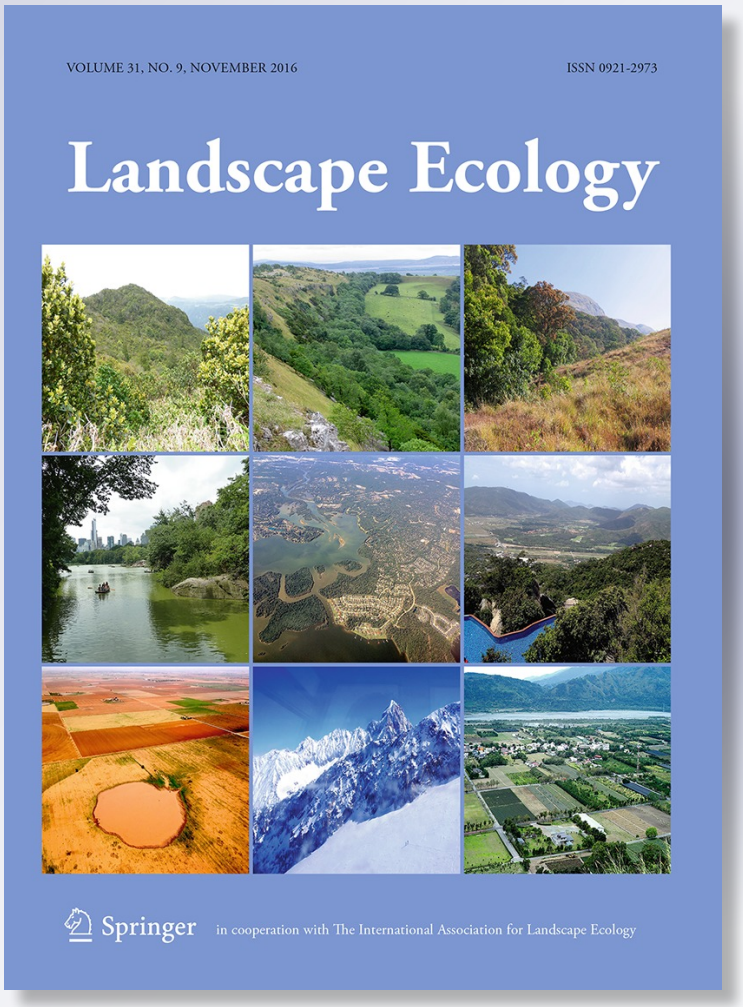

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RESEARCH ARTICLE

Biophysical influences on the spatial distribution of fire in the desert grassland region of the southwestern USA

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Abstract

Context Fire is an important driver of ecological processes in semiarid systems and serves a vital role in shrub-grass interactions. In desert grasslands of the southwestern US, the loss of fire has been implicated as a primary cause of shrub encroachment. Where fires can currently be re-introduced given past state changes and recent restoration actions, however, is unknown and controversial.

Objectives Our objective was to evaluate the interactive effects of climate, urban development, and topo-edaphic properties on fire distribution in the desert grassland region of the southwestern United States.

Methods We characterized the spatial distribution of fire in the Chihuahuan Desert and Madrean Archipelago ecoregions and investigated the influence of soil properties and ecological site groups compared to other commonly used biophysical variables using multi-model inference.

Results Soil-landscape properties significantly influenced the spatial distribution of fire ignitions. Fine-textured bottomland ecological site classes experienced more fires than expected in contrast to upland sites with coarse soil textures and high fragment content that experienced fewer fire ignitions than expected. Influences of mean annual precipitation, distance to road/rail, soil available water holding capacity (AWHC) and topographic variables varied between ecoregions and political jurisdictions and by fire season. AWHC explained more variability of fire ignitions in the Madrean Archipelago compared to the Chihuahuan Desert.

Conclusions Understanding the spatiotemporal distribution of recent fires in desert grasslands is needed to manage fire and predict responses to climate change. The use of landscape units such as ecological sites presents an opportunity to improve predictions at management scales.

Keywords Fire probability · Ecological sites · Soil properties · Desert grasslands · Chihuahuan Desert · Madrean Archipelago · Multi-model inference

Electronic supplementary material The online version of this article (doi:10.1007/s10980-016-0383-9) contains supplementary material, which is available to authorized users.

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Introduction

Grassland and shrub savanna landscapes across the globe are currently experiencing shrub expansion (Naito and Cairns 2011) as a result of factors including chronic, heavy grazing, climate, and seed dispersal by cattle and rodents (Van Auken 2000, 2009). All of

these factors can reduce fuel loads that ultimately lead to a loss of the fire-grass feedback that supports grass dominance (Scholes and Archer 1997; D'Odorico et al. 2012).

The restoration of fire-grass feedbacks is an important management priority in many grassland ecosystems (Beckage et al. 2005; Ansley and Castellano 2006). For example, removal of woody species though various means is often employed to trigger grass reestablishment and restore high fire frequencies (Halpern et al. 2012; Twidwell et al. 2013; Platt et al. 2015). The success of these efforts, however, depends on the potential fire probabilities across landscapes and regions (Beckage et al. 2005). The relationships between resource gradients, most importantly moisture, and fire probability have been used to infer how factors such as climate or topography constrain fire (Krawchuk and Moritz 2011; McWethy et al. 2013). While climate influences on moisture gradients have been explored in great detail (e.g., Whitman et al. (2015)), the contribution of soil profile properties is largely overlooked. A comprehensive understanding of the biophysical factors that constrain fire distribution at multiple scales is important context for understanding and planning fire management and restoration activities.

Biophysical variables that influence fuel load and quality are commonly employed to model fire distributions; hence, maps of vegetation, land cover, fuel characteristics and soil moisture have been used to predict fire properties (Krawchuk and Moritz 2011; Abatzoglou and Kolden 2013; Hawbaker et al. 2013; Van Linn et al. 2013; Krueger et al. 2015). Proxies for biophysical variables, such as elevation zones (Crimmins and Comrie 2004), ecological zones (Brooks and Matchett 2006), ecoregions (Dennison et al. 2014), and spectral variables (Poulos 2009; Hawbaker et al. 2013; Van Linn et al. 2013; Gray et al. 2014) have also been used to model fire distribution. Ignition probability is often included as lightning strike density and distance to roads or populated areas (Narayanaraj and Wimberly 2012; Yang et al. 2015).

At intermediate spatial scales, vegetation productivity and related fuel loads are closely tied to soil-landscape properties. The soil-geomorphic template exerts a major influence on vegetation via microclimate and the storage and delivery of water (Monger and Bestelmeyer 2006; Michaud et al. 2013). Subtle variations in physical soil properties can significantly influence vegetation change (Bestelmeyer et al. 2006) which may also dictate fuel characteristics. For example, the effect of fire on shrub cover can vary by soil type (Ansley et al. 2010). Fine scale soil properties, however, are rarely used to explain fire distribution (but see Dilts et al. (2009). Available water holding capacity (AWHC) integrates the effects of several soil properties, such as soil texture, gravel content, and bulk density, on soil moisture resources available to support plant production. The relationships between soil, landform, climate and vegetation are classified using ecological sites in the United States (Bestelmeyer et al. 2009). Ecological sites differ in potential vegetation and management strategies and are made spatially explicit via soil mapping. While the importance and use of fire is known to vary among ecological sites, these classes are not generally used to explain fire distribution. Spatial representation of ecological sites is achieved through the correlation of site classes to soil survey map units in the US, which provides a potentially valuable tool for understanding fire patterns and communicating information about fire to users.

In the desert grassland region of the southwestern US, encompassing the Chihuahuan Desert and adjacent woodland ecoregions, there is controversy about where fires placed important constraints on shrub dominance prior to European colonization or where fires can currently be introduced given past state changes and restoration actions (such as managed grazing to restore grass cover and shrub removal) that occurred in the nineteenth and twentieth centuries (Dick-Peddie 1993; McPherson 1995; Turner et al. 2003; Drewa et al. 2006). A significant portion (66 %) of the desert grassland region is currently believed to represent a moderate (43 %) or high (23 %) vegetation departure class with respect to historic conditions (LANDFIRE 2012b), most of which currently has a high shrub cover that is assumed to have supported fire-prone grasslands in pre-European times (LANDFIRE 2012a). Based on this and other assessments, government agencies have supported restorations actions (such as shrub/tree removal and grazing deferment) across the region that are ultimately intended to restore fire-grass feedbacks (e.g., Restore New Mexico; http://www.blm.gov/nm/st/en/prog/restore_new_mexico/what_is_restore.html).

Region-wide studies on the biophysical controls of fire in the desert grassland region to inform

management prioritization, however, do not exist. Such studies in the Mojave Desert to the west of our study area suggest that most fires and the largest areas burned occur in mid-elevation shrublands (Brooks and Matchett 2006), whereas fires in the adjacent Sonoran Desert are more likely in low elevation zones with low road density (Gray et al. 2014; Gray and Dickson 2015). In general, the spatial distribution of fires in the southwestern US is largely controlled by the accumulation of fuels which is closely tied to antecedent precipitation patterns (Crimmins and Comrie 2004). We posit that soil properties interact with precipitation to influence fire frequencies over long time scales.

Our objective was to evaluate the interactive effects of climate, urban development, and topo-edaphic properties on fire distribution in the desert grassland region. Specifically, we asked if information about the topo-edaphic properties, captured in ecological site classes, AWHC, and topographic variables could improve our understanding of the spatial distribution of fires over the last 33 years, thereby informing restoration priorities and the potential use of fire. We predicted that areas within the region that receive relatively low mean annual precipitation would have low fire frequencies irrespective of AWHC (Fig. 1). Similarly, areas with high rainfall would have a high frequency of fire irrespective of AWHC because adequate fuels are available on all soils. Areas of intermediate rainfall, on the other hand, would be most sensitive to variation in AWHC, and high values would be associated with high frequencies but low values would yield too little vegetation production to support frequent fires. In addition, we tested two a priori predictions about fire distribution in desert grasslands. (1) Fire distributions will vary by ecological site classes as a result of differences in vegetation communities and soil-landscape properties. (2) While precipitation is expected to be important for explaining fuel loads and fire distributions, we predict that soil AWHC will account for a significant amount of variation in fire probability in all zones of the desert grassland region. Tests of these predictions will not only produce valuable information for managing fire in southwestern US desert grasslands, but also evaluate the potential utility of soil profile data for modelling fire distributions in similar semiarid ecosystems.

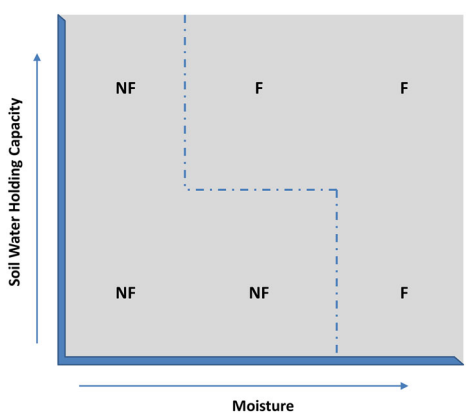

Fig. 1 Conceptual diagram of where fire happens in the desert grassland region of the southwestern United States based on the potential soil moisture space. *F* represents a high likelihood of fire occurring and *NF* indicates a low fire likelihood

Methods

Study area

The study area circumscribes the desert grassland region of the southwestern United States. Desert grasslands are warm temperate grasslands generally associated with the Chihuahuan Desert that sit at the transition between desert scrub and higher elevation woodlands, including portions of Arizona, New Mexico, Texas, and northern Mexico (Brown 1994; McClaran and Van Devender 1995). To encompass desert grassland extent in the US, we evaluated fire distributions in the Chihuahuan Desert and Madrean Archipelago ecoregions described by the level III Environmental Protection Agency (EPA) Ecoregions. Preliminary evaluation of fire ignition data showed significant differences in available data in the Texas portion of the Chihuahuan Desert so we evaluated fire distributions in Texas separately from the New Mexico and Arizona portion of the Chihuahuan Desert. After separating the Chihuahuan Desert by political boundaries, there were a total of three subregions within the desert grassland region: Madrean Archipelago, the portion of the Chihuahuan Desert in Arizona and New Mexico and the portion of the Chihuahuan Desert in Texas (Fig. 2).

The Madrean Archipelago receives approximately half of its precipitation via low intensity frontal systems during the winter months and the other half via high-intensity rainfall during the North American

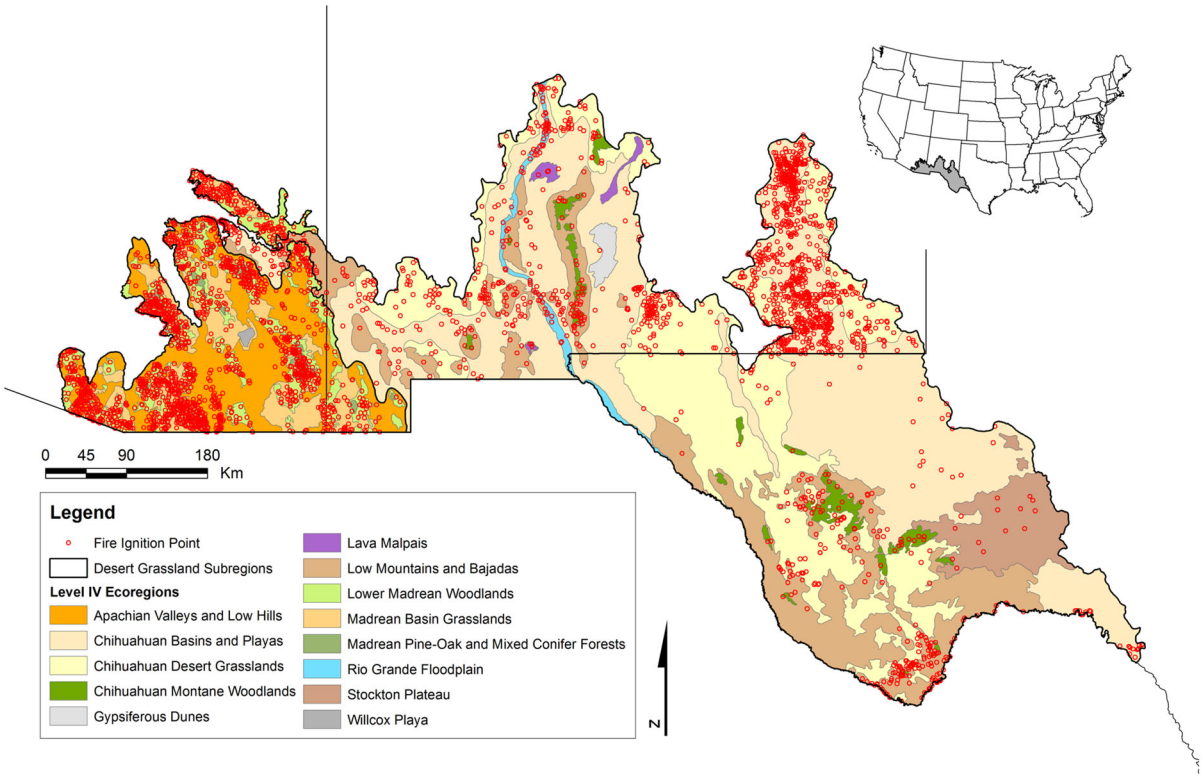

Fig. 2 Desert grassland region and fire ignition points for fires >0.4 ha in size

Monsoon season in the summer months. Precipitation in the Chihuahuan Desert is primarily received as summer rainfall during the monsoon season, and there is a decrease in the proportion of precipitation that falls as winter rain from west to east across this region. The study area is part of the Basin and Range physiographic province with elevation ranging from 340 m asl near Del Rio, TX to 3267 m on Mount Graham west of Safford, AZ. Vegetation ranges from riparian communities in river floodplains to subalpine forest in high-elevation mountains and includes a variety of grasses, forbs, shrubs, leaf succulents, cacti and salt-tolerant species. A diverse suite of soils comprise the region ranging from high sand to high clay with depths from very shallow to very deep and some soils having high salt content or coarse fragment content.

We evaluated fire distributions at two scales of the desert grassland landscape. The first scale encompassed all ecological zones within the desert grassland region. High elevation ecological zones that support mixed conifer forests and woodlands have been the focus of previous fire studies in this region (Swetnam and Baisan 1996; Meunier et al. 2014), but characterization of fires across all ecological zones has not been performed for this area. Our remaining objectives were focused on desert grasslands so we removed level IV ecoregions representing high-elevation landscapes comprised of coniferous vegetation and woodland: Madrean Pine-Oak Mixed Conifer Forests, Lower Madrean Woodlands and Chihuahuan Montane Woodlands. We refer to the remaining zones as 'low elevation' zones.

Fire data

Fire data were compiled from three sources: the Federal Fire Occurrence Website (WILDFIRE; http://wildfire.cr.usgs.gov/firehistory/data.html) (version February 25, 2013), Monitoring Trends in Burn Severity (MTBS; http://www.mtbs.gov/), and the Texas Forest Service (Curt Stripling, personal communication). The WILDFIRE database contained fire data for lands managed by the following federal

agencies: BIA, BLM, BOR, USFS, FWS, and NPS. Data were available for the period 1980–2012. MTBS data represented all currently completed MTBS fires that occurred from 1984 to 2012 on public and private lands. Texas Forest Service data included large wildfires (~405 ha) from 1985 to 2012. Small fires are commonly removed from wildfire probability models to avoid problems associated with the quality and availability of information without significant negative implications for model effectiveness (Parisien et al. 2012); thus, we evaluated fires greater than 0.4 ha in size.

Prior to spatial analysis, all data layers were projected to the same geographic coordinate system (GCS NAD83). Calculations of area were made using an Albers Equal Area USGS version spatial projection. Fire polygons from MTBS and the Texas Forest Service data were converted to point data representing the centroid of each delineated polygon. Points from each dataset were clipped to the extent of the study area before merging. We followed recommendations similar to those outlined in Brown et al. (2002) to remove potentially erroneous data. This included the removal of duplicate entries, false alarm fires, and fires without dates. For duplicated entries of the same fire, we kept entries with the most complete data and assumed a fire with more area burned represented the most up-to-date information.

Environmental covariate data

Biophysical variables included in models were categorized into those representing ignition sources and those representing physical conditions. Physical conditions were modeled with PRISM climate data (PRISM Climate Group 2012), soil survey, topographic data derived from a digital elevation model, and EPA ecoregions. Average monthly climate data (800 m spatial resolution) included maximum average monthly temperature (MT) and mean annual precipitation (MAP) over the 30-year period of 1981–2010. Seasonal precipitation was also calculated to facilitate interpretation of fire distributions as follows: peak fire season (months = MJJ), fall (ASO) and winter/spring (NDJFMA). Gridded Soil Survey Geographic (gSSURGO) data (10 m spatial resolution) were obtained for the study area and pre-summarized attributes of available water holding capacity (AWHC) for the 0–50 cm depth and root zone depth were evaluated as predictors (Soil Survey Staff 2014). Ecological site information was also extracted from gSSURGO and the dominant ecological site for each soil map unit was grouped according to soil-landscape attributes available in the Ecological Site Information System (ESIS) database following the key in Supplementary Fig. 1. Definitions used for each group are presented in Supplementary Fig. 1. Soil map units that were not correlated to ecological sites were assigned to ecological site groupings (Ecological site group) using soil map unit descriptions of soil profiles available in soil surveys or official soil series descriptions. Topographic variables were derived from the National Elevation Dataset with 30 m spatial resolution. Variables included elevation, percent slope, and aspect. Aspect is commonly transformed from circular data format to a linear variable representing southern or southwestern aspects (Faivre et al. 2014; Hegeman et al. 2014). We chose to use southerliness, which was calculated as

$$\mathrm{abs}(\mathrm{abs}((\mathrm{Aspect} - 180)/180) - 1) \quad (1)$$

where abs is absolute value.

Predictor variables representing ignition sources included lightning strike data and distance to roads and rails. Gridded lightning strike data representing the total number of strikes per year from 1991 to 2012 (4 km spatial resolution) were obtained from the National Oceanic and Atmospheric Administration National Centers for Environmental Information website (available at ftp://eclipse.ncdc.noaa.gov/pub/Data_In_Development/lightning/grids/countPerYear/, verified 30 June 2015) to represent potential for natural ignitions. Data from each year were averaged for each raster cell to summarize the spatial distribution of lightning across the study area. Distance to nearest road or rail was calculated to represent human accessibility as a source of ignition. Road and rail data were obtained from 2010 US Topologically Integrated Geographic Encoding and Referencing (TIGER) system line files (available at https://www.census.gov/geo/maps-data/data/tiger-line.html, verified 30 June 2015). All roads were obtained at the county level for all counties within the study area and merged into one layer along with national rail data that were clipped to the extent of the study area boundary. The shapefile was converted to a raster layer with 30 m spatial resolution and Euclidean distance to roads was calculated.

Spatial analyses

Points representing the centroid of each PRISM pixel within our study area were used to extract AWHC data for the 0–50 cm soil depth. These data represented the feature space of MAP and AWHC across the entire study area and were used to interpret the distribution of the same information for fire ignition points as a test for our predictions synthesized in Fig. 1. We performed Chi square tests to evaluate non-random distributions in fire frequencies with respect to ecological site groups.

We identified burned areas within the desert grassland region by merging polygons from the MTBS and Texas Forest Service databases. Because fire polygons were not available for the WILDFIRE database, we assumed a circle would be the most unbiased method of estimating areas that had burned by creating a circle around each fire ignition point that was equal the total area burned by each fire, similar to Hegeman et al. (2014). We then added a 1 km buffer to the assumed burned areas and merged these areas with the other databases. Random points were then sampled in the assumed unburned zones of each sub area to match the number of fire ignition points in each sub area. All points representing fire ignition and random unburned points were spatially joined with environmental covariate data.

Logistic regression

We used case–control multiple logistic regressions to evaluate the influence of biophysical variables on fire distribution by comparing points in burned and a similarly-sized, randomly selected population of points occurring in unburned areas. This approach has been used to evaluate the influence of predictor variables on fire occurrence in other studies (Kalabokidis et al. 2007; Narayanaraj and Wimberly 2012; Hegeman et al. 2014). We used R (R Core Team 2014) to compare a suite of models defined a priori following the multi-model inference approach described in Anderson (2008). Explanatory variables representing topography, climate, soil and ignition source and model specifications can be found in Supplementary Tables 1–3.

Only fires from the WILDFIRE database were used for regression to avoid the potential for spatial errors. Variables with Pearson correlation coefficients >|0.4| were not included in the models. Each variable appeared in an equal number of models to enable multi-model inference. We ranked logistic regression models using the corrected Akaike's Information Criterion (AICc) (Anderson 2008). Every logistic regression model developed was applied to spatial covariate data to produce probability maps of fire ignition. Model averaged predictions for each subregion-fire season combination were calculated using a linear combination of probability maps by multiplying AICc weights by corresponding probability as suggested by Cade (2015) (B Cade, pers. comm.). Relative variable importance was calculated by comparing parameter estimates that were standardized by their partial standard deviation and averaged by AIC weight (Cade 2015). Using standardized estimates for comparing relative variable importance is appropriate for generalized linear models with nonlinear link functions and accounts for the contribution of individual predictors within each candidate model (Cade 2015).

To test our prediction that soil property influences will vary for peak versus nonpeak fires, we divided fires into peak fire season and nonpeak fire season for separate regression models. Peak fire season was similar for both ecoregions and we defined it as May, June, and July because these months had the greatest number of fires and more area burned than other months (Fig. 3; Littell et al. (2009)).

Results

Spatial patterns of fire

The Madrean Archipelago subregion occupies an area one- fifth the size of other subregions in the desert grassland region; however 51 % of the fires that occurred between 1980 and 2012 were in this zone (Table 1). Analysis of fire distributions across all ecoregions showed that disproportionately more fires occurred in high elevation zones than low elevation zones within the desert grassland region (Table 1). Evaluation of level III ecoregions showed that the Chihuahuan Basins and Playas accounted for the largest proportion of fires in the Desert Grassland region followed closely by Lower Madrean Woodlands (Supplementary Table 4). Few fires occurred in

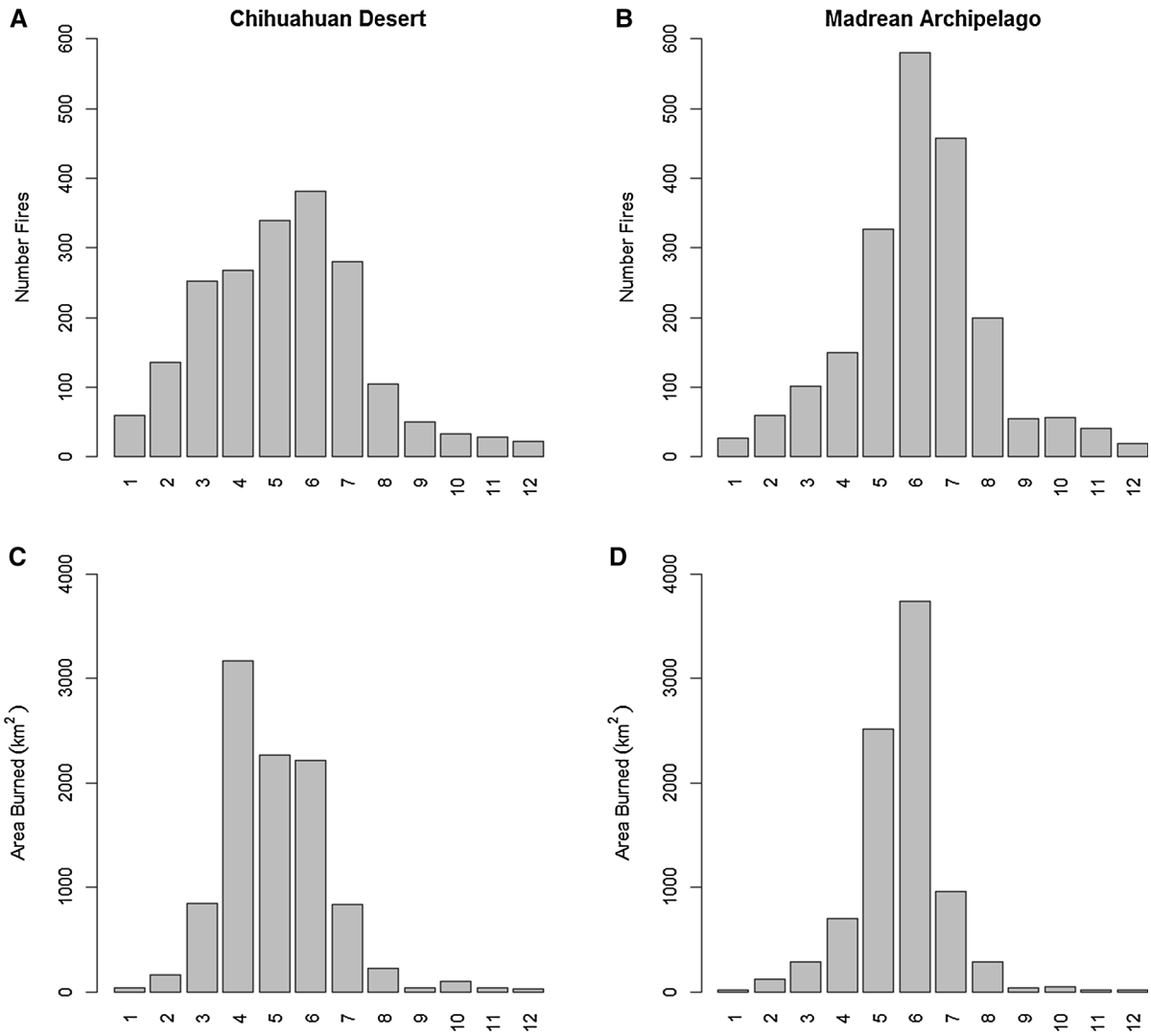

Fig. 3 Monthly distribution of fire counts (**a**, **b**) and hectares burned (**c**, **d**) in the Chihuahuan Desert and Madrean Archipelago between 1980 and 2012

Gypsiferous Dunes, Wilcox Playa, Lava Malpais and the Stockton Plateau.

The distribution of fires in low elevation zones was significantly different between ecological site groups in all three subregions (Table 2). In the Madrean Archipelago, shallow (not sandy) and clayey ecological site groups experienced more fires than expected and accounted for 46 % of the Chi square statistic. Fewer fires than expected occurred on loamy-skeletal sites (skeletal sites have greater than 35 % coarse fragments in subsurface soil horizons; Supplementary Fig. 1), which accounted for 21 % of the Chi square statistic. Bottomlands of the Chihuahuan Desert experienced more fires than expected in both subregions and accounted for large portions of respective Chi square statistics. Fewer fires occurred in loamy-skeletal and sandy ecological site groups of the Chihuahuan Desert in both subregions and in the loamy ecological site group of the Chihuahuan Desert subregion in TX. The Chihuahuan Desert subregion in TX also had more fires than expected in the shallow (not sandy) ecological site group.

Table 1 Summary of fires within three subregions of the desert grassland region from 1980 to 2012. Low elevation zones excluded the following level IV EPA ecoregions: Madrean Pine-Oak Mixed Conifer Forests, Lower Madrean Woodlands and Chihuahuan Montane Woodlands

Subregions	Area (km^2)	Proportion study area (%)	Number of fires >0.4 ha	Proportion fires (%)	Density of fires >0.4 ha (km^2 per fire)
All					
Madrean Archipelago subregion	39,650	19.5	2079	51.2	19
Chihuahuan Desert_AZNM subregion	72,272	35.6	1634	40.2	44
Chihuahuan Desert _TX subregion	91,298	44.9	347	8.5	263
Desert grassland region	203,220		4060		
Low elevation only					
Madrean Archipelago subregion	26,615	14.2	850	30.8	31
Chihuahuan Desert _AZNM subregion	71,301	38.2	1607	58.2	44
Chihuahuan Desert _TX subregion	88,979	47.6	302	10.9	295
Desert grassland region	186,894		2759		

Relative variable importance

MAP was the most consistent variable related to the fire ignitions in Madrean Archipelago and the Chihuahuan Desert of AZ and NM (Fig. 4). Interestingly, MAP was not related to fire ignitions in the Chihuahuan Desert of TX. MAP was four times more important than AWHC during the peak fire season in the Madrean Archipelago and it was also more important than AWHC in the Chihuahuan Desert subregions in AZ and NM (×17) and TX (×3). AWHC was the second most important variable in Madrean Archipelago and was 1.5 times more important than distance to road and six times more important than southerliness. For the Chihuahuan Desert of AZ and NM, elevation and MAP contributed similarly to the models and were four and five times more important, respectively, than distance to road. Distance to road was the most important variable in the Chihuahuan Desert of TX, ranging from 17 to 86 times more important than other variables.

Similar to the peak fire season, fires in the Madrean Archipelago during nonpeak season were largely related to MAP which was seven times more important than AWHC. AWHC in Madrean Archipelago was five times more important than southerliness and 35 times more important than distance to road. Elevation was marginally more important than MAP and distance to road for explaining nonpeak fires in the Chihuahuan Desert of AZ and NM. Slope and AWHC had similar contributions to the models. Slope and elevation were the primary variables explaining fire ignitions in the Chihuahuan Desert of TX. AWHC, MAP and southerliness contributed little to fire ignition probabilities in the Chihuahuan Desert of TX during the nonpeak fire season.

Fire probability models

In the Madrean Archipelago, fire probability was higher in areas adjacent to high elevation regions and lower in basins (Fig. 5a). The most notable areas of high fire probability in the Chihuahuan Desert of AZ and NM were in the Pecos River valley. Other areas of high probability were near the Gila National Forest in western portion of this subregion. Distance to road was more important for explaining fire ignition probability throughout the Chihuahuan Desert compared to the Madrean Archipelago and was the dominant explanatory variable in TX.

Nonpeak fire probabilities were similar to peak fire probabilities (Fig. 5b). The patterns were nearly the same in the Madrean Archipelago but with generally lower probabilities throughout the region. Fire ignition probabilities in the western portion of the Chihuahuan Desert of AZ and NM were also visibly lower with the influence of distance to road having greater importance. The Pecos River valley had the highest probability of fire across the Chihuahuan Desert of AZ and NM. There was a widespread increase in fire probability across the Chihuahuan Desert of TX compared to peak fire seasons, with a notable increase in high probability areas in the southern portion of the state.

Table 2 Chi-square test for fire ignition points from 1980 to 2012 to evaluate ecological site groups in three low elevation desert grassland subregions. Ecological site groups are described in Supplementary Fig. 1

Ecological site group	Area (km^2)	% Area	Fires	O (fires)	E (fires)	O-E	Proportion of χ^2
Madrean Archipelago							
Bottomland	2728	0.11	70	0.09	85	−15	0.04
Clayey	6277	0.25	242	0.3	197	45	0.16
Clayey-skeletal	994	0.04	23	0.03	31	−8	0.03
Gypsum-affected	151	0.01	0	0	5	−5	0.07
Loamy	6538	0.26	169	0.21	205	−36	0.09
Loamy-skeletal	1610	0.06	24	0.03	50	−26	0.21
Salt-affected	205	0.01	1	0	6	−5	0.07
Sandy	1646	0.06	45	0.06	52	−7	0.01
Sandy-skeletal	21	0	0	0	1	−1	0.01
Shallow (not sandy)	5295	0.21	224	0.28	166	58	0.3
Total	25,464	1	798	1	798	DF	9
						χ^2	66.6
				Critical value (p = 0.05)			16.9
AZ and NM portion of Chihuahuan Desert							
Bottomland	4535	0.07	198	0.13	101	97	0.32
Clayey	3814	0.06	93	0.06	85	8	0
Clayey-skeletal	442	0.01	8	0.01	10	−2	0
Gypsum-affected	3457	0.05	115	0.07	77	38	0.06
Loamy	19,190	0.28	539	0.35	429	110	0.1
Loamy-skeletal	12,301	0.18	138	0.09	275	−137	0.24
Salt-affected	219	0	10	0.01	5	5	0.02
Sandy	13,890	0.2	165	0.11	310	−145	0.24
Sandy-skeletal	162	0	3	0	4	−1	0
Shallow (not sandy)	11,148	0.16	276	0.18	249	27	0.01
Total	69,157	1	1545	1	1545	DF	9
						χ^2	284.7
				Critical value (p = 0.05)			16.9
TX portion of Chihuahuan Desert							
Bottomland	5218	0.06	35	0.12	17	18	0.23
Clayey	2185	0.03	5	0.02	7	−2	0.01
Clayey-skeletal	3222	0.04	6	0.02	11	−5	0.03
Gypsum-affected	3486	0.04	1	0	12	−11	0.12
Loamy	18,546	0.21	30	0.1	61	−31	0.2
Loamy-skeletal	14,276	0.16	30	0.1	47	−17	0.08
Salt-affected	1022	0.01	2	0.01	3	−1	0.01
Sandy	1747	0.02	2	0.01	6	−4	0.03
Shallow (not sandy)	37,602	0.43	178	0.62	124	54	0.29
Total	87,304	1	289	1	289	DF	8
						χ^2	79
				Critical value (p = 0.05)			15.5

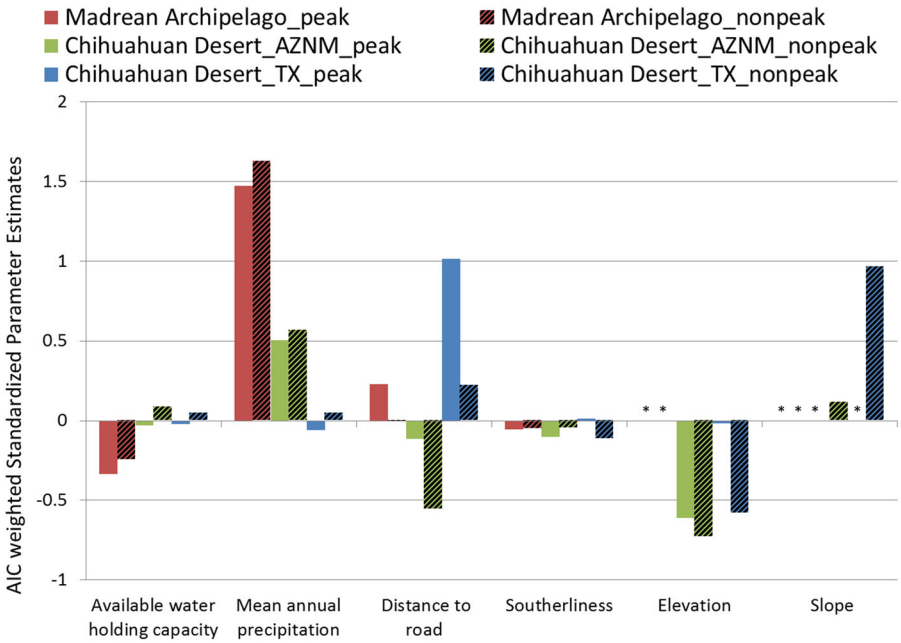

Fig. 4 AICc weighted parameter estimates for main effects summarized from standardized logistic regression results of fire ignition points in low elevation zones of the desert grassland region for fires in peak and nonpeak seasons. Chihuahuan Desert_AZNM is the portion of the Chihuahuan Desert in Arizona and New Mexico, Chihuahuan Desert_TX is the portion of the Chihuahuan Desert in Texas, peak represents fires models during peak fire months of May, June and July and nonpeak represents fire models of nonpeak fire months (all other months). Variables with an *asterisk* were not included in the model due to correlation with other included variables

Influence of soil moisture space on fire distribution

The potential soil moisture space proposed in Fig. 1 was compared to real data across the study area to explore the combined effects of AWHC and MAP on fire occurrence. Our sample did not include areas with low enough precipitation to exclude fires (Fig. 6). Fires greater than 0.4 ha occurred throughout the possible range of MAP and AWHC in the study area (Fig. 6a). There was, however, a noticeable shift in the occurrence of large fires (>405 ha; Fig. 6b) that suggests a MAP threshold (~300 mm) may control where large fires occur. This study area did not have cases of concurrently high MAP and high AWHC, suggesting the need to expand this concept to a larger geographic area to fully explore its utility for explaining fire ignitions. For water-limited systems, including soil properties in the moisture and plant production continuum will likely improve our understanding of the biophysical space for fire [e.g., Whitman et al. (2015)].

Discussion

Spatial distribution of fires in the desert grassland region

We found more fires in high elevation zones compared to low elevation zones across the desert grassland region which is similar to the spatial patterns reported for the Mojave Desert (Brooks and Matchett 2006; Hegeman et al. 2014). Increased fire activity in the Madrean Archipelago was likely due to the influence of the bimodal precipitation regime (winter and summer) compared to the unimodal pulse of summer precipitation resulting from the North American Monsoon in the Chihuahuan Desert subregions. Generally higher elevations in the Madrean Archipelago also contribute to overall increased precipitation and reduced evaporative demand than in the Chihuahuan Desert. Together these factors result in the potential for more fine fuels in the Madrean Archipelago and can explain the differences in fire regimes. Another

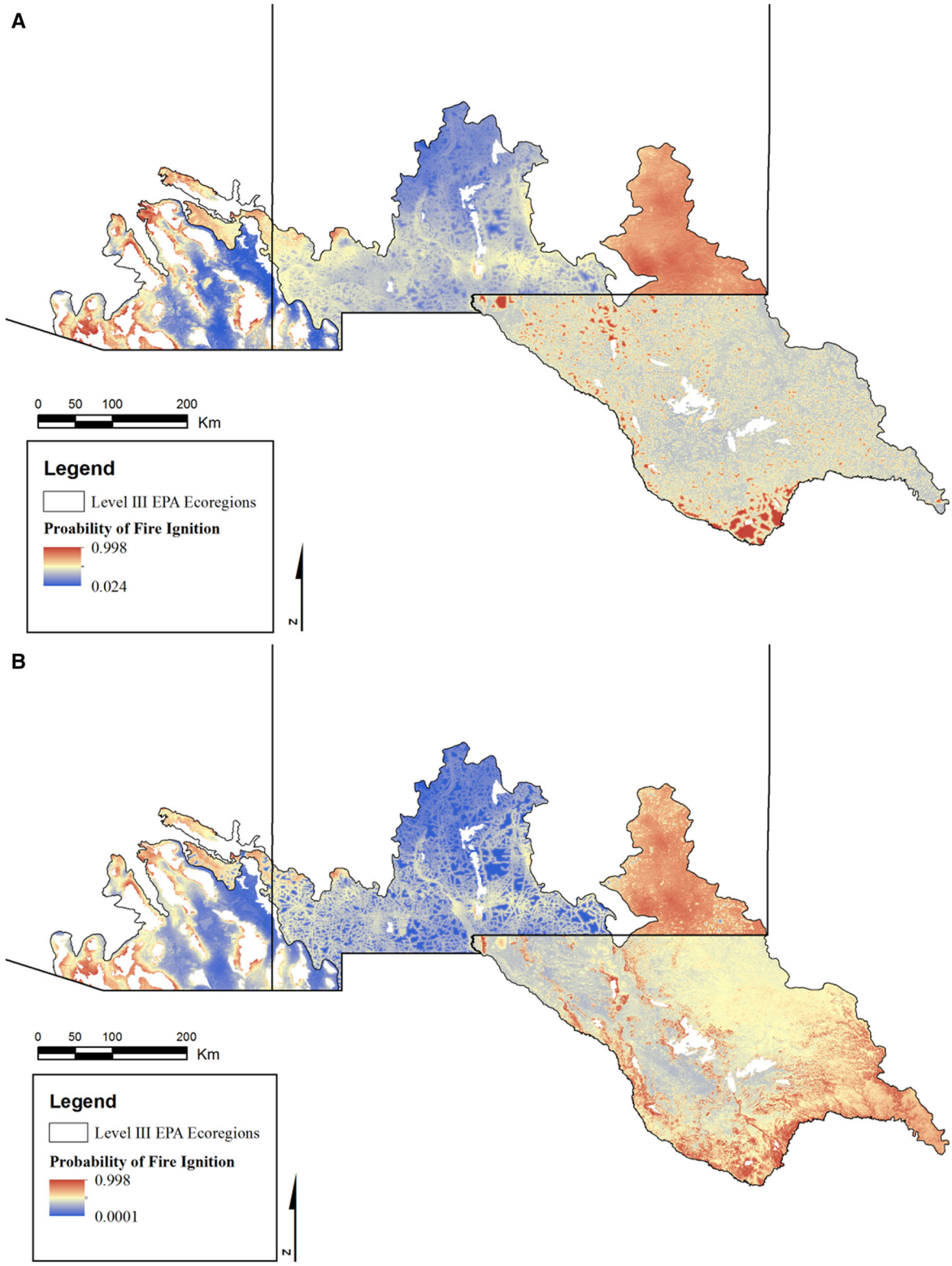

Fig. 5 Ignition probability for peak (**a**) and nonpeak (**b**) fires in the desert grassland region based on data from 1980 to 2012

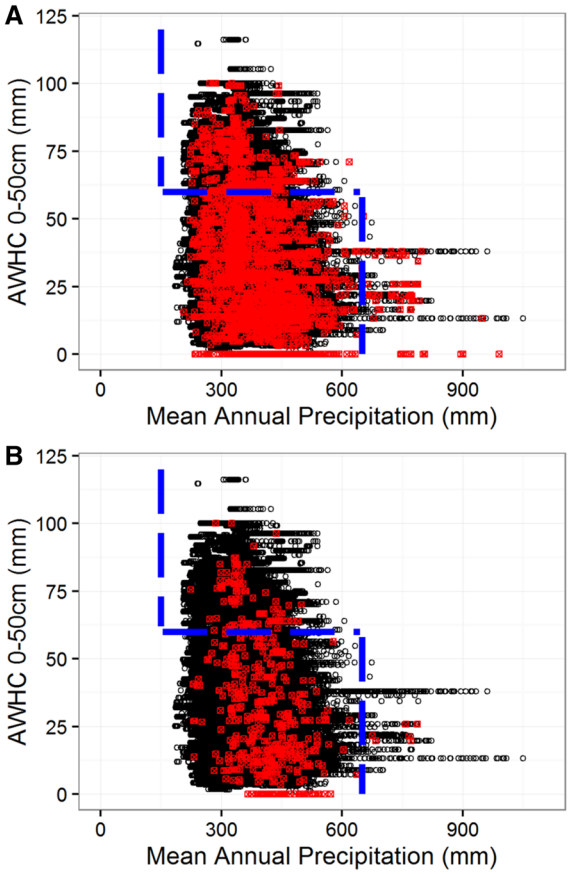

Fig. 6 Measured data plotted in the context of the conceptual figure presented in Fig. 1 for the desert grassland region for fires greater than 0.4 ha (**a**; n = 4060) and greater than 405 ha (**b**; n = 627). Data from fire ignition points are *red squares* and *gray circles* represent the feature space of environmental data for the entire study area

obvious trend was the dearth of fire ignitions in TX (Fig. 2). The low number of ignitions in TX may reflect differences in land ownership and possibly management. Furthermore, fire ignition points on private land are likely not recorded in federal databases of fire occurrence (e.g., WILDFIRE).

Ecological site influence on fire distribution

Soil-landscape properties captured in groupings of ecological sites across the study area were significantly related to the spatial distribution of fire on the landscape. These units describe the physical environment that is directly related to potential vegetation that governs fire probability. Analyses that couple landscape units to temporal variations in precipitation and temperature provide a powerful approach for predicting fire occurrence. Similarly, detailed ecoregions (level IV) can capture much of the variability in fire distribution at even broader spatial scales.

Our analyses further indicated that specific soil properties had an influence on fire distribution. In the Madrean Archipelago, shallow soils had more fire ignitions than expected. Shallow soils can support higher perennial grass cover relative to deep soils in the Chihuahuan Desert (Khumalo et al. 2008) which may have contributed to fuel continuity and explain the increased number of fire ignitions. Ecological site groups representing soils with low AWHC, such as loamy-skeletal and sandy soils, had fewer fires than expected which may reflect a low availability of continuous fine fuels. In contrast, the clayey ecological site group had more fire ignitions than expected, perhaps because these soils are relatively productive for perennial grasses (https://esis.sc.egov.usda.gov/ESDReport/fsReport.aspx?id=R042XA061NM&rptLevel=all&approved=yes&repType=regular&scrns=&comm=).

In both Chihuahuan Desert zones, a significant number of fires occurred in bottomland areas that receive run-on water from adjacent landscape positions. Bottomland areas and other closed drainages within the Chihuahuan desertscrub communities are known to have high productivity of perennial grasses including *Pleuraphis mutica*, *Sporobolus airoides*, and *S. wrightii*) (Brown 1994); https://esis.sc.egov.usda.gov/ESDReport/fsReport.aspx?id=R042XA057NM&rptLevel=all&approved=yes&repType=regular&scrns=&comm=). Areas dominated by these grasses are known to support relatively frequent fires (Neuenschwander and Wright 1984; Cox 1988). High concentrations of soluble salts, on the other hand, can strongly limit plant production and therefore fine fuels. Fewer fires than expected occurred in salt-affected and gypsum-affected soils of Madrean Archipelago and the Chihuahuan Desert subregion in TX, but the opposite was true for the Chihuahuan Desert subregion in AZ and NM, perhaps because these areas also receive high amounts of run-on water.

Our results indicate that information about soil properties represented in detailed soil maps provide predictive and interpretable information about fire occurrence. Dilts et al. (2009) explored the use of soil infiltration and AWHC to explain wildfire distributions in southeastern Nevada, but found the

information to be of little importance. It is likely that the coarse soil data they were using (STATSGO) was insufficient for modeling fire probability at the scale of their study. We used AWHC from the SSURGO database which has much finer resolution of soil properties and may explain why we found an influence of AWHC in our study (Fig. 4). Further refinement of the influence of soil moisture on fire occurrence will likely improve prediction models. For example, Krueger et al. (2015) used a comprehensive network of soil moisture measurements to model fire distributions in the Southern Great Plains of Oklahoma. They found that the fraction of available water in the upper 40 cm of the soil profile was strongly linked to wildfire occurrence during the growing season because it is closely tied to live fuel moisture. While extensive networks of dynamic soil moisture status clearly have potential for real-time fire warning programs and management decisions, this type of data is unavailable for most areas of the globe. Alternatively, soil property maps are available for large parts of the global rangelands and have great potential to improve estimates of soil moisture conditions in the absence of measured values.

Findings from the exploratory analysis with Chi square tests suggest meaningful patterns of fire ignition and fuel characteristics are related to soil properties; however, these analyses do not account for contributions of individual biophysical parameters. These questions were further explored in biophysical logistic regression models.

Biophysical drivers of fire by subregion and fire season

Summary of major differences

MAP had the biggest effect on fires in the Madrean Archipelago which resulted in fire distributions that were relatively easy to interpret and consistent with previous work (Crimmins and Comrie 2004). In contrast, evaluation of fires within the Chihuahuan Desert showed that relationships between biophysical drivers and fire frequencies varied between the NM/AZ and TX subregions as well as the Madrean ecoregion and, in some cases, relationships were counterintuitive. Varying interactions of drivers across space and data availability issues have likely produced the patterns we observed. Below, we discuss our interpretations with regard to each driver.

Distance to road

The effect of roads and expanding wildland-urban interface are known to increase wildfire ignitions (Narayanaraj and Wimberly 2012; Faivre et al. 2014). We found higher fire probabilities farther from roads in the Chihuahuan Desert subregion in TX and Madrean Archipelago subregion, but fire probability was highest close to roads in the Chihuahuan Desert of AZ and NM. Hegeman et al. (2014) found that fire occurrence was more likely close to roads in the Mojave Desert when all fire sizes were included and conversely more fires were found farther from roads when only large fires were modeled. Hawbaker et al. (2013) also found that fires were more likely away from roads in the Chihuahuan Desert when only large fires were considered. Our results reflect models with all fire sizes included; however, comparison to other studies in the region suggests that drivers of fire ignition may be different if we had modeled different fire sizes separately. Differences in road density might also explain these contrasting influences. Low road density increases the likelihood that fire ignitions will become large fires in the lower Sonoran Desert in southwestern Arizona (Gray et al. 2014).

The greatest density of fire ignitions in the Chihuahuan Desert of AZ and NM were in the Pecos River valley (Figs. 1, 6). This area features a large number of oil and gas drilling pads visible in satellite imagery. The Pecos River Valley is part of the Permian Basin, which is an oil and gas producing area that covers large portions of southwestern TX and southeastern NM (http://www.rrc.state.tx.us/oil–gas/major-oil–gas-formations/permian-basin/). The average road density in the low elevations of Pecos Valley of NM is approximately two times greater than for other portions of the Chihuahuan Desert in AZ and NM, which may reflect the energy development in this area.

Topography

In the Madrean Archipelago, fire ignition probability had a strong positive relationship with elevation. Higher elevations in Madrean Archipelago experience

increased MAP and lower evapotranspiration which promotes fine fuels. The density of fire ignition in the southwestern US often increases with elevation (Brooks and Matchett 2006) which reflects the resource gradient found in these systems (Whittaker and Niering 1965). In contrast, the high probability of fire in the Pecos River Valley of NM is lower in elevation than most other areas of the subregion. The inverse relationship between fire probability and elevation in the Chihuahuan Desert of AZ and NM reflects the large number of fires that occurred there during our study period and suggests some combination of other drivers were responsible for the fires in the Pecos Valley. One plausible explanation for varying effects of elevation, aside from differences in fuel characteristics, is that natural ignitions are more likely at high elevation whereas human ignitions are more likely at low elevations.

Aspect controls microclimate and vegetation. Five of our six models showed that fire probability was higher on north aspects, which has also been reported in the Mojave Desert (Hegeman et al. 2014) and portions of southern California (Faivre et al. 2014). In the low elevation zones of the desert grasslands, north-facing slopes are more likely to produce fine fuels than south-facing slopes because there is more available moisture.

Soil AWHC

The inverse relationship between AWHC and fire probability in the Madrean Archipelago seems counterintuitive to the notion that soils with higher AWHC should support more fine fuels. However, shallow soils can perch water near the surface which can be productive for grasses. Relatively small contributions of AWHC to fire probability models in the Chihuahuan Desert may be due to the important roles of other factors, such as road density, elevation and slope. Additionally, AWHC may not capture soil properties that affect vegetation and fuels as well as ecological site classifications. Furthermore, using AWHC does not account for the soil moisture conditions at any given time which significantly affects fuel moisture conditions and our ability to predict fire occurrence (Krueger et al. 2015). In summary, our data did not support our prediction that AWHC would account for a significant amount of variation in fire probability in all zones of the desert grassland region.

Climate

While there were noticeable influences of MAP on fire distributions in two of the subregions, seasonal patterns of climate are also likely to be important. For example, the bi-modal precipitation in the Madrean Archipelago combined with higher MAP promotes vegetation growth and increased fine fuels. Moreover, increased MAP in the Madrean Archipelago was also associated with more lightning strikes compared to other subregions (data not shown).

In addition to oil and gas development-related ignitions, higher MAP (346 mm) may explain why there are more fine fuels and fire ignitions in the Pecos Valley compared to other portions of the Chihuahuan Desert (289 mm). Interestingly, this difference in MAP also crosses the 300 mm threshold in large fires shown in Fig. 6. Average MAP for the Chihuahuan Desert in TX was 339 mm, which suggests fire ignitions may be more numerous than reflected in our data.

Data availability and political jurisdiction

We suspect that differences in the fire ignition points among the Chihuahuan Desert subregions may be related to differences in data availability. More data are potentially available from Arizona and New Mexico, which have extensive amounts of state and federally managed land, compared to Texas, which is largely private land. Furthermore, the large shift in land ownership across the New Mexico-Texas boundary may influence fire management as a result of social influences like risk and liability concerns associated with prescribed burning (Toledo et al. 2014). Our dataset included both natural and human caused fires, including prescribed burns; however, there is not currently a database of prescribed fire on private land in Texas (C. Stripling, pers. comm). Hence, data availability may explain the dearth of fire ignitions in the Chihuahuan Desert of TX even though it has large areas of energy development and higher MAP. Another dataset focusing on a more recent timeframe and more complete data could be considered in future studies (Short 2015).

Ignition differences by season

Fire probability models often omit nonpeak fires (Abatzoglou and Kolden 2013) or develop models that

include from fires from all seasons (Brooks and Matchett 2006; Riley et al. 2013). Our data showed that probability models for the Madrean Archipelago were similar for peak and nonpeak seasons, whereas model structure in subregions of the Chihuahuan Desert varied by season. Different fire ignition patterns resulting from varying seasonal influences of drivers illustrate the need to evaluate fire distributions by season of burn to improve our understanding of fire regimes and support more accurate predictions. This finding supports the concept that fire modeling efforts should consider seasonal variability of fires to better understand drivers of fire.

Conclusions

We modeled fire ignition probability in the desert grassland region over a 33 year period. Our analyses illustrate that soil and ecological site information can be used to refine landscape-level models of fire distribution in some settings with better resolution than many of the current ecoregional classifications. These data will be useful for land managers who want to develop long-term landscape management goals and shorter-term burn plans. The broad-scale heterogeneity represented in fire probability maps (Fig. 5) also indicates vast differences in the potential use of fire across the desert grassland region and within subregions. The biophysical correlates of the current distribution of fire can provide a basis for prioritization of management interventions to restore fire-grass feedbacks and to interpret the success of past restoration treatments. For example, certain ecological sites, such as bottomlands in the Chihuahuan Desert or higher-elevation shallow soils in the Madrean Archipelago, might be better targets of restoration investments than other ecological sites. Such interpretations must be tempered by the fact that the study region has been subject to many undocumented human impacts, including over a century of varying grazing histories and restoration attempts. Such impacts complicate interpretations about the potential use of fire.

The large differences in dominant explanatory variables that we observed among subregions highlight the need for landscape-specific analyses. Differences in biophysical drivers of fire probability by subregion suggest multi-scale assessments may be necessary to better understand and model the influence of moisture gradients on fire distribution. Interactions of explanatory variables likely mask the influence of individual drivers which can lead to inaccurate inferences if only a few drivers are considered. Variability of seasonal controls of fire distribution highlight the importance of modeling fire probability in both peak and nonpeak fire seasons to represent patterns specific to each. Incorporation of social aspects of fire management, such as land ownership and political boundaries, may also contribute to more accurate models.

The use of soil-landscape properties and ecological sites to explain fire distribution may be especially useful in the face of changing climate conditions because soils control moisture availability and plant production, that in turn affects fire susceptibility. Identifying landscape units where fire is unlikely to occur has strong implications for land managers across the globe making decisions about whether or not fire will be a useful management tool for restoring landscapes to grassland conditions.

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