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Annual precipitation drives fire occurrence across sub-humid and semi-arid ecological gradients

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Abstract

Fire is an integral part of semiarid to moderately humid ecosystem dynamics in North America. The biogeographical settings in which fires readily occur are affected by global processes like climate change, as well as local and regional characteristics such as terrain, proximity to human infrastructure, and vegetation structure. Increasing numbers and severity of fires today requires high-resolution and accurate predictions of fire probability. Species distribution models (SDM) allow researchers to identify environmental predictors of fire and depict the probability of fire occurrence. We applied a Maximum Entropy (Maxent) SDM to identify fire predictors and fire risk across a broad biogeographic humid to semi-arid climate gradient within the state of Texas. We used 15 years (2001-2016) of remotely sensed fire occurrence data, along with 13 biophysical variables representing climate, terrain, human activity, and landcover to generate multiple models. Annual precipitation was the primary predictor of fire occurrence, followed by elevation and landcover. After projecting fire probability onto three climate scenarios, we found moderate change in fire distribution. Humid and sub-humid areas had higher probabilities of fire occurrence while arid regions had lower probabilities under those scenarios. Overall, the linkage between fire occurrence and annual precipitation suggests that climate-driven fire probabilities will be variable under projected future climates.

Highlights

- In our North American study region, annual precipitation is predictive of fire occurrence across a sub-humid to semi-arid biogeographic gradient.
- Future climates under a variety of carbon emission scenarios may impact the probability of fire occurrence across environmental gradients.
- Species Distribution Models (SDMs) provide a means of exploring the interactions between fire occurrence and biogeographic characteristics of landscapes.

Keywords: climate, distribution modeling, drylands, fire, MaxEnt, North America, precipitation, remote sensing

Introduction

Global climate change is predicted to change fire activity across all terrestrial biomes, with fires generally increasing in number and severity (Dennison et al. 2014). In particular, fire activity in sub-humid and semi-arid drylands has increased alongside climate change and human activity over the past 50 years (Ortega et al. 2012). These trends in fire activity vary based on historical climate, vegetation type, and topography, each influencing fire-environment interactions (Parisien et al. 2012). Given projected changes in fire activity due to changes in the fire environment, there is an accompanying need to study how these changes may affect current and future fire occurrences (Morgan et al. 2001).

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Sub-humid and semi-arid drylands comprise 41% of all terrestrial land area, and 34% of the world's population resides within these biomes (Maestre et al. 2012, SCBD 2013). Vegetation productivity in these regions is frequently water-limited and subjected to regular drought and fire activity (Vallejo et al. 2012). Temperature and precipitation seasonality determine effective length of the fire season, and temperature extremes hasten or slow the drying of fuel (Dale et al. 2001). Although climate warming is expected to alter climate controls on fire occurrence globally (Flannigan et al. 2009), a regional understanding of climate controls and their future shifts is necessary to prepare for alternative fire-regime futures.

Landscape characteristics and human activity are additional factors that modify the distribution of fire occurrence (Cary et al. 2006, Syphard et al. 2007, Mann et al. 2016). Landscape characteristics such as terrain (e.g., elevation, ruggedness) and landcover influence the distribution of fire because they create fine-scale mosaics of heterogeneous fire environments (Kane et al. 2015). Human activity is also well-known to influence fire distribution directly through fire ignitions and suppression and indirectly through climate and fuel modification (Archibald 2016). Modeling fire occurrence using climate and landscape characteristics will help identify important predictors of fire distribution and their relative importance to accurately modeling fire distribution across the sub-humid to dryland gradient.

One method of parsing out interactions within the fire environment is using species distribution models (SDMs) to estimate the probability of fire occurrence and quantify the relative importance of local fire environments under present and future climate scenarios (Parisien and Moritz 2009, Parisien et al. 2014). Using recorded fire occurrences and descriptive environmental variables, these models allow for flexible applications across different scales and regions (Parisien et al. 2012). In previous work, SDMs and similar models have been successfully used to model fire occurrence across heterogeneous landscapes with varying spatial extents (Parisien et al. 2012, Young et al. 2017). However, there is a knowledge gap regarding the drivers of fire across ecoregion transitions such as the sub-humid to semi-arid gradient. Harnessing the spatial distribution of recorded fires, we sought to assess whether the landscape and climatic controls that mediate wildfire across the sub-humid to dryland transition can be predicted.

We applied SDMs to determine the extent to which climate and landscape characteristics are capable of predicting fire occurrences across a broad biogeographical gradient that represents a sub-humid to dryland transition within the state of Texas. We ask how well climate alone predicts fire occurrence and how including landscape characteristics modify the prediction of fire occurrence. We hypothesize that climate is a major driving factor of the distribution of fire occurrence, but that including landscape characteristics will improve model performance, especially because humans now cause most fire ignitions and are responsible for fire suppression (Syphard et al. 2007, Parisien et al. 2016). We project the probability of fire occurrence on multiple future climate scenarios to determine where we should anticipate changes in the distribution of fire occurrence.

Materials and Methods

We used a Maximum Entropy (MaxEnt) SDM with fifteen years of remotely sensed fire occurrence data to explore the influence of environmental characteristics in predicting fire occurrences in the south-central United States under contemporary and predicted future climate scenarios. We accomplished this by modeling the probability of fire occurrence using a suite of climate, terrain, human, and landcover descriptors at a one-km resolution across the sub-humid and semi-arid climate gradient in the U.S. state of Texas, an area encompassing nearly 696,000 km^2. We generated fire occurrence models for each of four descriptive variable categories and compared them to a fifth comprehensive model using all variables. With these five models, we sought to identify geographic areas with different fire prediction levels and the specific variables contributing to these fire occurrences. Finally, we applied our comprehensive fire prediction model to future climate scenarios to identify how they may potentially change fire probability.

Study Area

Within the south central United States, the state of Texas encompasses a transition from humid to semi-arid environments. Precipitation ranges from more than 1,340 mm in the east to less than 360 mm annually in the west (Hijmans et al. 2005). Elevation across the transition ranges from sea level to 2667 m (USGS 2008). Texas is home to three of the ten most populous cities in the U.S. and has population densities ranging from 1007 people per sq. km in Harris County to 0.03 people per sq. km in Loving County (Census Bureau, 2010). Vegetation across the state changes along a longitudinal precipitation gradient, with pine and mixed pine-hardwood forests dominating the humid eastern portions of the state, oak-juniper savannas prevailing in the central part of the state, and mixed shrub-grasslands covering the western part of the state (McMahan et al. 1984). The cartographic boundary for the state was defined based on the 2010 Census boundary and served as the clipping and processing extent for all predictor variables.

Remotely sensed fire occurrence

Fire occurrence data were collated from the USDA Active Fire Mapping Program (https://data.fs.usda.gov/geodata/maps/active-fire.php) between the years 2001 and 2016, and includes 135,798 fires. These fire occurrences are generated from the MODIS active fire product, which detects fire in one km pixels using middle-infrared and thermal infrared brightness (Giglio et al. 2009). This platform provides daily detections across the United States. Prior to input into our model, data were clipped to retain only the points

within the study area, and data from multiple years were merged into a single comprehensive dataset for the 15 year time period. It is worth noting that due to the temporal resolution of the detection platform, data do not include fires that started and were suppressed prior to the sensor flyover. Additionally, the spatial resolution of the detection algorithm inhibits our ability to identify small fires that were suppressed before they reached a measurable extent (~1km). Thus, our data do not include short or small fires. We used the kernel density function in ArcMap to visualize the density of fire occurrences as the number of fires per 1km^2 raster cell within our study area.

Environmental variables

Environmental variables were selected from a suite of climate, terrain, landcover, and human variables chosen for their hypothesized influence on fire occurrence and spread (Table 1). To remove redundancy, improve model performance, and improve interpretation of results, we conducted a correlation analysis of 21 environmental variables, reviewed those variables that were strongly correlated ($r > 0.7$), and retained the variables most strongly connected to fire occurrence or variables that were previously used in SDM studies of fire occurrences, so as to make direct comparisons among studies (Merow et al. 2013) (Table S1). Removing highly correlated variables improves interpretation of MaxEnt models and projection of models into future climate scenarios (Braunisch et al. 2013). Seven variables were removed. The remaining 13 variables were grouped into four variable sets based on their representation of climate, terrain, human, and landcover influence (categories are marked in Table 1). All environmental variables were downloaded at, or resampled to, a 1 km^2 spatial resolution and projected to NAD1983 projected coordinate system.

The climate dataset was sourced from a suite of 19 biologically important climate variables provided in the WorldClim database of global weather and climate data (Hijmans et al. 2005) (Table S1). The climate variables are interpolated at approximately one km spatial resolution from 50 year averages of climate station data across the globe. All the climate data were downloaded at 30 arc-second resolutions and resampled to a one km spatial resolution. These data are commonly used for SDMs and are particularly well-suited for occurrence-based distribution modeling (Booth et al. 2014). After conducting the correlation analyses, we selected 5 variables that are particularly relevant to fire occurrence in our study area. Given the seasonality of drought and fire-conducive weather, measuring mean annual temperature, and the maximum temperature of the warmest month provide context for the hot conditions that regularly occur and vary across the area. Additionally, the selection of annual precipitation and the mean temperatures of the wettest and driest months provide insight into the role that precipitation and the interactions between temperature and precipitation have in predicting fire occurrence.

To determine potential effects of terrain on fire occurrence, we used a suite of terrain variables

Table 1. Environmental variables for Maxent representing a suite of climate, terrain, landcover, and human influences on fire occurrence. Each variable was computed or acquired at one km resolution.

Category	Variable	Units	Reference
Climate	Mean annual temperature	C	WorldClim (Hijmans et al. 2005)
	Max Temperature of Warmest Month	C	WorldClim (Hijmans et al. 2005)
	Mean Temperature of Wettest Quarter	C	WorldClim (Hijmans et al. 2005)
	Mean Temperature of Driest Quarter	C	WorldClim (Hijmans et al. 2005)
	Annual Precipitation	mm	WorldClim (Hijmans et al. 2005)
Terrain	Elevation	m	US National Elevation Database (USGS 2017)
	Topographic Roughness Index		Calculated from elevation from US National Elevation Database (USGS 2017)
	Solar Radiation		Calculated from elevation from US National Elevation Database (USGS 2017)
	Aspect	Direction	Calculated from elevation from US National Elevation Database (USGS 2017)
Landcover	Landcover Type	Categorical	National Landcover Database (USGS 2011)
Human	Population Density	Pop. per km^2	2010 US Census (Census 2010)
	Distance to Nearest Municipal Boundary	km	Municipal Boundaries Dataset (USGS 2017)
	Distance to Nearest Major Road	km	National Road Atlas (USGS 2017)

generated from a one km digital elevation model (DEM) from the US National Elevation Dataset (USGS 2008). These calculated and derived rasters included elevation, topographic roughness index, and aspect. Topographic roughness, which represents elevation difference between adjacent pixels (Riley 1999), is the squared root of the sum of squared differences in elevation between a center cell and its eight neighbors. Roughness values ranged from near zero, representing relatively smooth topography, to 1227, indicating large abrupt variations in adjacent elevation. Aspect was calculated using the DEM to determine the direction of a slope as a range between 0 and 360 degrees. Solar radiation is a measure of the insolation of a landscape in watt hours per square meter per year. This measure reflects direct sun exposure and, therefore, indirectly captures evapotranspiration and drying potential for fine fuels.

We incorporated the influence of human activity and infrastructure on fire occurrence by calculating population density (population per km^2), distance to the nearest city boundary (km), and the distance to the nearest interstate highway (km) These data were downloaded January 2017 as shapefile vectors and converted to rasters matching the $1km^2$ spatial resolution as the rest of the data using ArcMap. Population density was extracted from the 2010 census block data (Census of Population and Housing, 2010), locations of municipal boundaries were also obtained from the USGS Municipal Boundaries shapefile, which includes all incorporated and unincorporated local communities within the state. The distances to the closest interstate and nearest community were calculated using the Euclidian Distance tool in ArcMap to identify isolated areas with large distances between municipalities or interstate highways, which may be more removed from firefighting capabilities and road access.

The influence of landcover type on fire occurrence is tied to the fuels present and the contiguity of fuel for fire spread (Littell and Gwozdz 2011). We used the 2011 National Landcover Database (Homer et al. 2015) to define the primary form of landcover present. This database contains 20 classes of landcover types including shrublands, coniferous forests, urban, and water, among others. We resampled this layer to the $1km^2$ spatial resolution and clipped it to the extent of the study area. Using categorical data for landcover type allows the MaxEnt model to test the predictivity of the various discrete classes within the dataset.

Modeling the probability of fire occurrence

We modeled the probability of fire occurrence using the Maxent model (Version 3.3.3k) (Phillips et al. 2006). Maxent is an SDM, which uses values of environmental variables at occurrence points to build algorithms to predict probability of occurrence (Elith et al. 2011). Maxent uses randomly selected background points within the extent of the study area as pseudo absences to calibrate entropy algorithms. To validate a Maxent model, the occurrence data are split into training and testing datasets. The model generates response curves that are used to map the relative probability of occurrence within the area of study and outputs a list of the relative contributions of each input variable (Phillips et al. 2006).

We ran a series of models to estimate the probability of fire occurrence and projected models onto three future climate scenarios. The series included a comprehensive model with all variables and one sub-model for each variable suite: climate, terrain, human impact, and landcover. By partitioning these variable suites, we were able to identify regions of dissimilar estimation and compare the influence of each variable suite with a model that included all of the variable suites. For each model, response curves and jackknife calculations were performed to identify variable predictive ranges and to calculate variable importance. Variable response curves detail predictivity across the range of values for each environmental variable. Jackknife calculations generate independent Maxent models using only one variable and compare the predictivity of that single variable model to the overall model using all of the environmental variables. Additionally we defined 135,000 background points, which provide the Maxent model a random sample of values from within the study extent to compare the environmental data of the occurrence points to the background points for fitting model algorithms (Elith et al. 2011). We withheld a random sample of 20% of the occurrence points for model validation (i.e. for the testing dataset).

Assessing model performance

We assessed model performance using the area under the receiving operator curve (AUC) (Elith et al. 2011). This curve represents the plot of sensitivity of true positives over the specificity of false positives. AUC values range from 0.5, where the model prediction is no better than any random selection of test points, to one, which represents perfect model prediction accuracy (Phillips et al. 2006). Previous work in using SDMs for modeling fire occurrence found that models with an AUC greater than 0.6 are considered informative (Parisien and Moritz 2009). Additionally, the percent contributions of each variable are calculated to provide insight in the relative predictivity of each input into the model. To identify areas with differing model results, we calculated a series of anomaly maps - the prediction from the comprehensive model minus the prediction from the model using each variable category. The resulting raster values are zero where there is no difference between predictions, negative where the comprehensive model had a lower probability of occurrence than the other models, and positive where the comprehensive model had a higher probability of occurrence than the other models.

Modeling future climate predictions

In order to predict changing probabilities of fire occurrence given future climates, we projected our models into various future climate scenarios. We used the NOAA Geophysical Fluid Dynamics Laboratory Climate Model 3 (GFDL-CM3) (Griffies et al. 2011). This climate model has been used for previous studies

in Texas, and is well suited for analyzing precipitation and temperature at the state and regional level (Rainwater 2013). We selected three climate scenarios generated from the climate model to represent the best case (RCP26), middle case (RCP45), and worst case (RCP85) emission scenarios for 2050. Each of these scenarios was clipped to the boundary of the study area and added as a projection in our Maxent model. We calculated anomaly maps between modern and future projections of probability of fire occurrence to evaluate change in probability of fire occurrence.

Results

Density of fire occurrences

Fifteen years of remotely-sensed fire occurrences in our study area showed the distribution of fire across the semi-arid to sub-humid gradient (Figure 1). There was a high density of fire occurrences in the pine and mixed pine-hardwood forests in the sub-humid to humid east and there were relatively few remotely-sensed fire occurrences in the mixed shrub-grasslands in the semiarid west, except in a few places like the Davis Mountains hosting a cooler wetter landscape than the surrounding arid lowland desert. In the oak-juniper savannas in the central region, there were heterogeneous densities of fires ranging from regions of extremely high fire occurrence to many regions with extremely low fire occurrence. There were also a few high density fire occurrences in the thorn shrub and subtropical woodlands of the south.

Modeling fire occurrences

Modeling fire occurrences with SDMs showed that the comprehensive model had the highest AUC, and therefore predictability, followed by the climate, terrain, landcover, and human impacts models, respectively (Table 2). The human impacts model did not reach the AUC model threshold of 0.6.

The comprehensive model predicted higher probability of fire occurrence in the central, eastern, and coastal portions of the state, as well as a particularly high area in the Davis Mountains surrounded by very low probability in the arid west (Figure 2). This is similar to the climate and terrain sub-models (Figure 2B,C), which also predicted higher probabilities of fire occurrence across the eastern, central, and coastal regions of the state and in the Davis Mountains region in the arid west. The human impacts model showed a surprisingly high probability across most of the state and moderate levels near major roadways (Figure 2D). The landcover model primarily

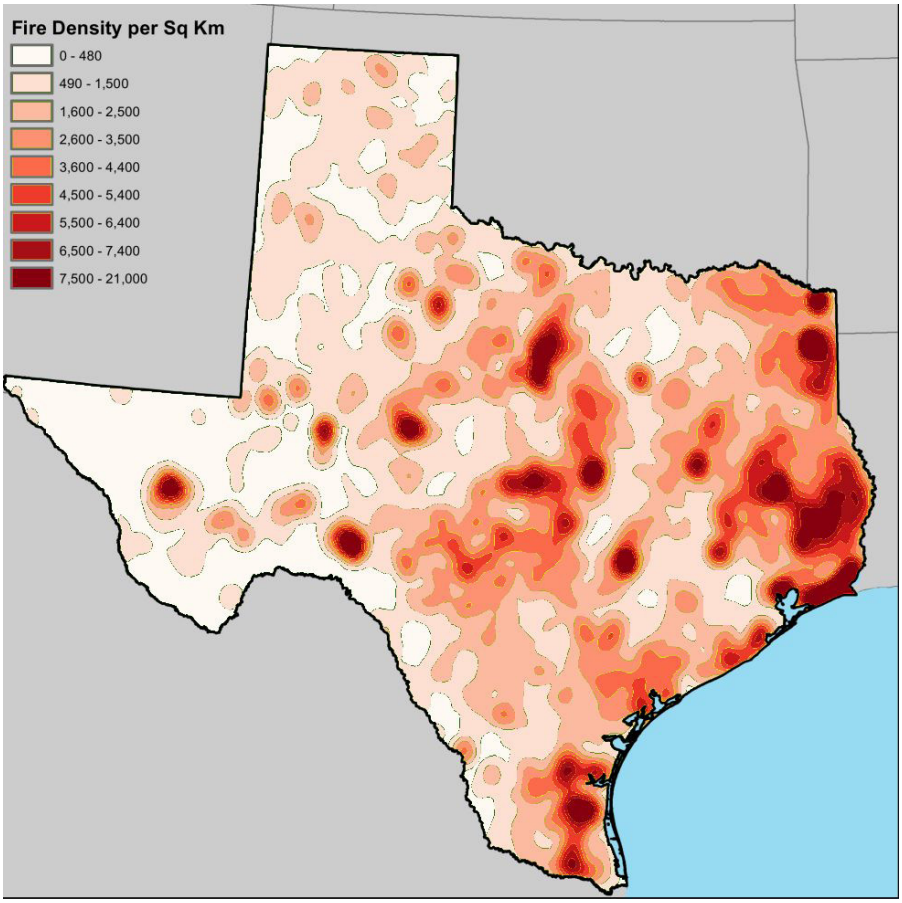

Figure 1. Kernel density of the 135,798 fires detected between 2001-2016 by the MODIS Active Fire Monitoring Program in occurrences per square kilometer across the state of Texas. Areas of darker red indicate higher densities of fire, while lighter areas indicate regions of lower fire density.

Table 2. Variable importance for the comprehensive model and the four type models for fire occurrence across Texas. Area under the receiving operating characteristic curve (AUC is shown for each model). Variables used to build each model, their percent contribution to the model, and their permutation importance are listed next to the model type and its AUC.

Model	AUC	Variable	Percent Contribution	Permutation Importance
Comprehensive	0.681	Annual Precipitation	53.4	55.5
		Elevation	11.1	5.5
		Landcover Type	8.2	11.3
		Max. Temperature of the Warmest Month	5.8	5
		Mean Annual Temperature	5.6	5.1
		Topographic Roughness	5.3	5.7
		Distance to City	4.6	6.4
		Mean Temperature of Driest Quarter	3.4	1.8
		Population Density	1.1	1.3
		Distance to Highway	0.8	0.8
		Mean Temperature of wettest quarter	0.7	1.4
		Solar Radiation Exposure	0.1	0.1
		Aspect	0	0
Climate	0.67	Annual Precipitation	76.1	64.9
		Max. Temperature of the Warmest Month	9.5	13.1
		Mean Temperature of Driest Quarter	7.6	4.3
		Mean Annual Temperature	4.8	13.6
		Mean Temperature of Wettest Quarter	1.8	4.2
Terrain	0.642	Elevation	92.1	86.5
		Topographic Roughness	7.3	11.9
		Solar Radiation Exposure	0.4	0.7
		Aspect	0.3	0.9
Human	0.581	Distance to City	77.1	62.7
		Distance to Highway	14.5	24.2
		Population Density	8.4	13.1
Landcover	0.616	Landcover Type	100	100

predicted fire occurrence in the eastern portions of the state dominated by pine forests (Figure 2D) and failed to identify regions of higher fire density in the central and southern portions of the state indicated by the distribution of fire density, as well as in the comprehensive, climate and terrain models.

Predictors of Fire Occurrence

Fire occurrence was best predicted in the comprehensive model by annual precipitation, accounting for 53.4% of the variation in that model (Table 2). In the climate model, annual precipitation was again the primary predictor of fire occurrence (76.1% model contribution) with the other climate variables contributing less than 23.7% to the model. The second and third highest contributing predictors of the comprehensive model, elevation and landcover respectively, were also top predictors of the terrain and landcover models. The human impact variables did not contribute meaningfully to the comprehensive model. As landcover was the only variable of the landcover model, it accounted for all variation within that model.

The environmental variables with higher overall contributions to the five models indicated the range of conditions that are associated with fire occurrence. The most predictive variable, annual precipitation, indicated that fires were more likely to occur in the central semi-arid to sub-humid transition zones and eastern sub-humid regions which receive over 450 mm of precipitation each year. While other climate variables did not contribute as much to the overall model prediction, fire was more probable in areas that had annual mean temperatures over 17°C and maximum temperatures of the warmest quarter under 37°C. Fire probability was also higher in dry semi-humid areas dominated by evergreen forests, deciduous forests, and shrublands (Figure 2).

Projected changes in future climate and fire occurrence

Future climate scenarios show an increase in mean annual temperature across our study area, averaging 0.24 C, 0.28 C, and 0.33 C for the RCP 25, RCP45, and RCP85 scenarios, respectively. Annual precipitation is projected to increase by an average of 37 mm, 20 mm, and 10 mm, respectively. Climate trends show the area

growing warmer and slightly wetter over time, even in the most optimistic of carbon emissions scenarios. These climate trends drive changes in predicted fire occurrence across this sub-humid to semi-arid gradient (Figure 3). Across climate scenarios, there was a consistent decline in fire probability across the central and northern part of the state, whereas the rolling plains and the high plains of the Panhandle and

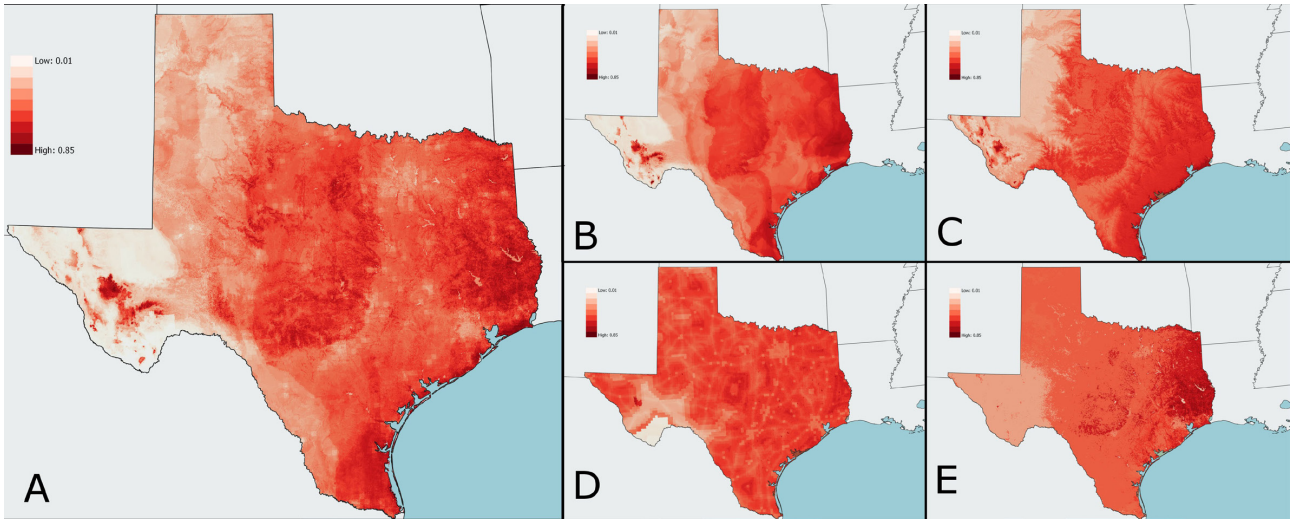

Figure 2. (A) Probability of fire occurrence across Texas for the comprehensive model. Fire probability for the climate (B), terrain (C), human (D), and landcover (E) models. Darker red indicates higher probability of fire, while areas of lighter red indicate regions of low probability of fire.

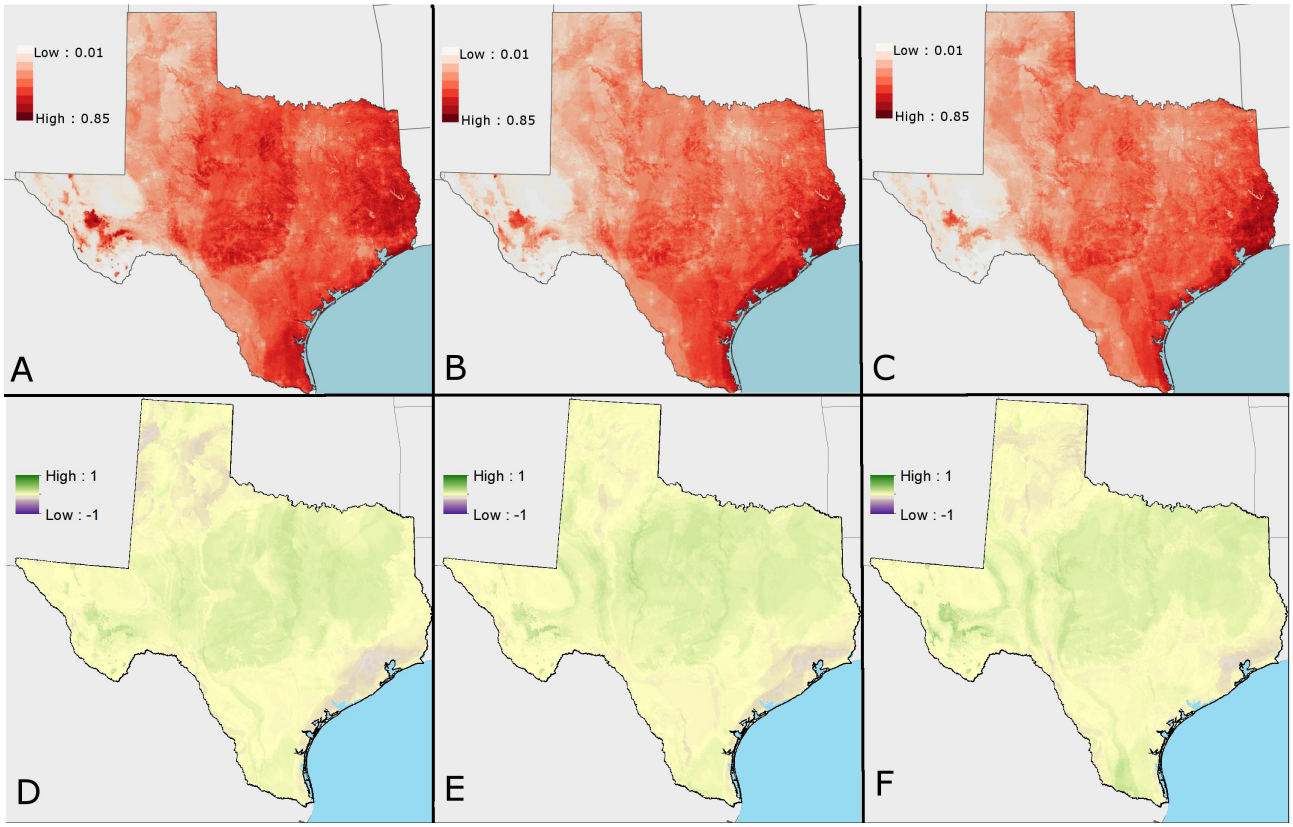

Figure 3. Projected climate model depicting probability of fire occurrence across Texas based on RCP26 (A), RCP45 (B), and RCP85 (C) future climate scenarios centered on the year 2050. Areas of darker red indicate higher probability of fire, while lighter areas indicate regions of lower probability of fire. Anomaly maps for the RCP26 (D), RCP45 (E), and RCP85 (F) future climate scenarios. Areas in purple indicate areas of increasing fire probability under future climate scenarios compared to the contemporary climate model (Figure 2B), while areas in green indicate areas decreasing in probability of fire occurrence under future climate scenarios.

the gulf prairies and marshes had an increase in fire probability (Figure 3).

Discussion

In a 15-year period with 135,798 remotely-sensed fires, annual precipitation was the strongest predictor of fire occurrence across the sub-humid to semi-arid transition in our study area. This corresponds with the previous work such as that of Parisien & Moritz (2009) which found similar relationships in fire-vegetation-climate analysis. The strong influence of annual precipitation on predicted fire occurrence likely reflects a linkage between increased precipitation and increased plant growth and biomass accumulation, which dries out in the droughty summer months and becomes susceptible to ignition. The rain-drought cycle has been identified in other, similar, semi-arid and sub-humid regions (Turner et al. 2008, Wang et al. 2016), and plays a critical role in where and when fires may occur. However, as our comprehensive and landcover models show, precipitation is more explanatory than vegetation type for the patterns we observed where landcover had a weaker predictive relationship with fire occurrence. This disconnect may illustrate that fuels and precipitation are both critical for fire to occur. Even when fuels accumulate, if they are not dry enough to ignite, then a fire is unlikely to occur and propagate.

Under several future climate scenarios, our models showed that the increase in temperature and precipitation drive heterogeneous changes in the probability of fire occurrence. While our fire occurrence projections consistently included widespread areas of reduced fire probability and pockets of increased fire probability, they do not inform on the expected severity of future fires. Fire severity is likely to increase over time, regardless of the numbers of fires, due to the higher overall temperatures and increased drought periods (Barbero et al. 2015). Future modeling efforts should include the impacts of these scenarios on fire severity in the study region.

Overall, we found that annual precipitation was a strong predictor of fire occurrence, both directly and through secondary linkages to ecological characteristics like vegetation type in sub-humid and semi-arid lands. The patterns we found support similar fire-vegetation-climate cycles identified in analogous ecological regions across the globe. Projection on future climate scenarios showed a widespread decrease in the probability of fire occurrence across great parts of the grasslands, juniper and oak woodlands, and live oak and mesquite savannah, as well as in the cross timbers and prairies in the central parts of the state most closely related to the transition zone between sub-humid to semi-arid environments. Interestingly, given the uncertainties that future climate conditions bring, we found little changes to the projections of the distribution of probability of fire occurrence among the three projected climate scenarios.

In light of the climate-driven drought cycles, land management practices provide the most direct modifications to the annual precipitation-fire occurrence relationship by inducing or suppressing fire and changing the vegetative structure. This is particularly relevant in sub-humid and semi-arid rangelands that are being converted into woodlands, cropland, and other ecosystems (Twidwell et al. 2013, Bestelmeyer et al. 2015, Leis et al. 2017). As an example, the conversion of grass-dominated rangelands to afforested woodlands introduces a shift in fire occurrence that may become more detectable to remote observation platforms such as the MODIS active fire product (Roy et al. 2008). Additionally, these changes in land-use and landcover across the Great Plains are a major driver in changes in carbon storage (Bouchard et al. 2011) and decreasing soil moisture (Zou et al. 2018). These vegetative shifts may therefore be managed to reduce the impact of climate shifts on fire occurrence and fire detection.

Rural landownership in Texas has been slowly trending away from traditional agricultural use and towards lifestyle and multiple-use management which generally shifts grassland ecosystems towards afforested juniper woodlands (Sorice et al. 2012). As these historical rangelands are encroached upon by woody plants, thus reducing the livestock carrying capacity while incurring significant land clearing costs to the landowner (Teague 2001). Our models of future projected increase in fire probability in the south-central plains combined with this continued landowner change suggests that we should continue to focus fire management efforts and vegetation restoration in the south-central plains.

Limitations to interpreting models projected on future climate scenarios include uncertainty surrounding the controls on fire occurrence with SDM, uncertainty in future climate scenarios, no-analog future climate conditions, and not incorporating future projections of vegetation cover or human impact. Projected models of future probability of fire occurrence are best viewed as representing the expectation of fire occurrence given various future suites of climate conditions. Future modeling efforts could include more in-depth projections for climate, landcover, and human impact variables over time and how such integrated future projections will change fire probability in the region.

SDMs like Maxent provide one method of exploring patterns of disturbance in modern and future climates, and are readily applicable to a variety of regional and global problems. Using tools like Maxent to explore fire occurrence as it relates to vegetation density, fire size, and comparing predictions based on annual climate, fire season, and fire size would all make for interesting future investigations. Another important aspect for future investigation includes evaluating different types of precipitation variables. Here, we chose to focus on annual precipitation because it was highly correlated to other precipitation variables. However, one study in the humid southeastern United States found precipitation seasonality or variability is more important than annual precipitation in that high moisture environment (Lafon and Quiring 2012). Thus, future research should investigate this in the sub-humid to semi-gradient across Texas. The global significance of

sub-humid and semi-arid lands makes them critical for understanding fire disturbance patterns in the modern environment and into the future. Understanding how environmental characteristics influence fire occurrence in these areas is a key component to facilitating their roles as natural ecosystem components when managing lands and to mitigating negative effects on these regions.

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Author Contributions

CTB, WER, CL, and ML conceived the ideas for this project. CTB and ML designed the methodology. CTB curated and analyzed the data, performed the analyses, designed the figures, and led the writing. ML supervised the work for this project. All authors contributed critically to the drafts and gave final approval for the manuscript.

Supplementary Material

The following materials are available as part of the online article at https://escholarship.org/uc/fb
Table S1. Table of all climate variables considered and tested for correlation prior to running the MaxEnt model.
Figure S1. Correlation matrix between bioclim variables used to select climate model inputs.

References

Archibald, S. (2016) Managing the human component of fire regimes: lessons from Africa. Philosophical Transactions of the Royal Society B, 371, 20150346.

Archibald, S., Roy, D.P., Wilgen, V., Brian, W. & Scholes R.J. (2009) What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Biology, 15, 613–630.

Beaty, R.M. & Taylor, A.H. (2002) Spatial and temporal variation of fire regimes in a mixed conifer forest landscape, Southern Cascades, California, USA. Journal of Biogeography, 28, 955–966.

Bestelmeyer, B.T., Okin, G.S., Duniway, M.C., Archer, S.R., Sayre, N.F., Williamson, J.C. & Herrick, J.E. (2015) Desertification, land use, and the transformation of global drylands. Frontiers in Ecology and the Environment, 13, 28–36.

Booth, T.H., Nix, H.A., Busby, J.R. & Hutchinson, M.F. (2013) bioclim: the first species distribution modelling package, its early applications and relevance to most current MaxEnt studies. Diversity and Distributions, 20, 1–9.

Bouchard, M., Butman, D., Hawbaker, T., et al. (2011) Baseline and projected future carbon storage and greenhouse-gas fluxes in the Great Plains Region of the United States. U.S. Geological Survey Professional Paper 1787. Available at https://pubs.usgs.gov/pp/1787/p1787.pdf.

Braunisch, V., Coppes, J., Arlettaz, R., Suchant, R., Schmid, H. & Bollmann, K. (2013) Selecting from correlated climate variables: a major source of uncertainty for predicting species distributions under climate change. Ecography, 36, 971–983.

Gary, G.J., Keane, R.E., Gardner, R.H., Lavorel, S., Flannigan, M.D., Davies, I.D., Li, C., Lenihan, J.M., Rupp, T.S. & Mouillot, F. (2006) Comparison of the sensitivity of landscape-fire-succession models to variation in terrain, fuel pattern, climate and weather. Landscape Ecology, 21, 121-137.

Census of Population and Housing (2010) United States Summary File 2, Texas (2002). doi:10.3886/icpsr13276.v1.

Dale, V.H., Joyce, L.A., McNulty, S., et al. (2001) Climate Change and Forest Disturbances. BioScience, 51, 723-734.

Dennison, P.E., Brewer, S.C., Arnold, J.D. & Moritz, M.A. (2014) Large wildfire trends in the western United States, 1984-2011. Geophysical Research Letters, 41, 2928–2933.

Elith, J., Phillips, S.J., Hastie T., Dud'ik, M., Chee, Y.E. & Yates, C.J. (2010) A statistical explanation of MaxEnt for ecologists. Diversity and Distributions, 17, 43–57.

Flannigan, M.D., Krawchuk, M.A., de Groot, W.J., Wotton, B.M. & Gowman, L.M. (2009) Implications of changing climate for global wildland fire. International Journal of Wildland Fire, 18, 483–507.

Griffies, S.M., Winton, M., Donner, L.J., et al. (2011) The GFDL CM3 coupled climate model: characteristics of the ocean and sea ice

simulations. Journal of Climate, 24, 3520–3544.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. & Jarvis A. (2005) Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology, 25, 1965–1978.

Lafon, C.W. & Quiring, S.M. (2012) Relationships of fire and precipitation regimes in temperate forests of the eastern United States. Earth Interactions, 16, 1-15.

Leis, S.A., Blocksome, C.E., Twidwell, D., Fuhlendorf, S.D., Briggs, J.M. & Sanders, L.D. (2017) Juniper invasions in grasslands: research needs and intervention strategies. Rangelands, 39, 64–72.

Lenihan, J.M., Drapek, R., Bachelet, D. & Neilson, R.P. (2003) Climate change effects on vegetation distribution, carbon, and fire in California. Ecological Applications, 13, 1667–1681.

Littell, J. S. & Gwozdz, R.B. (2011) Climatic water balance and regional fire years in the Pacific Northwest, USA: linking regional climate and fire at landscape scales. In: The landscape ecology of fire (ed. by D. McKenzie, C.M. Miller and D.A. Falk), pp. 117-139. Springer, Dordrecht.

Maestre, F.T., Quero, J.L., Gotelli, N.J., et al. (2012) Plant species richness and ecosystem multifunctionality in global drylands. Science, 335, 214–218.

Mann, M.L., Batllori, E., Moritz, M.A., Waller, E.K., Berck, P., Flint, A.L., Flint, L.E. & Dolfi, E. (2016) Incorporating anthropogenic influences into fire probability models: effects of human activity and climate change on fire activity in California. PLoS One, 11, e0153589.

Merow, C., Smith, M.J. & Silander, J.A. (2013) A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography, 36, 1058–1069.

Ortega, M., Saura, S., González-Avila, S., Gómez-Sanz, V. & Elena-Rosselló, R. (2011) Landscape vulnerability to wildfires at the forest-agriculture interface: half-century patterns in Spain assessed through the SISPARES monitoring framework. Agroforestry Systems, 85, 331–349.

Parisien, M-A., Miller, C., Parks, S.A., DeLancey, E.R., Robinne, F-N. & Flannigan, M.D. (2016) The spatially varying influence of humans on fire probability in North America. Environmental Research Letters, 11, 75005. doi: 10.1088/1748-9326/11/7/075005

Parisien, M-A. & Moritz, M.A. (2009) Environmental controls on the distribution of wildfire at multiple spatial scales. Ecological Monographs, 79, 127–154.

Parisien, M-A., Parks, S.A., Krawchuk, M.A., Flannigan, M.D., Bowman, L.M. & Moritz, M.A. (2011) Scale-dependent controls on the area burned in the boreal forest of Canada, 1980-2005. Ecological Applications, 21, 789–805.

Parisien, M-A., Parks, S.A., Krawchuk, M.A., Little, J.M., Flannigan, M.D., Gowman, L.M. & Moritz, M.A. (2014) An analysis of controls on fire activity in boreal Canada: comparing models built with different temporal resolutions. Ecological Applications, 24, 1341–1356.

Parisien, M-A., Snetsinger, S., Greenberg, J.A., Nelson, C.R., Schoennagel, T., Dobrowski, S.Z. & Moritz, M.A. (2012) Spatial variability in wildfire probability across the western United States. International Journal of Wildland Fire, 21, 313-327.

Phillips, S.J., Anderson, R.P. & Schapire, R.E. (2006) Maximum entropy modeling of species geographic distributions. Ecological Modelling, 190, 231–259.

Roy, D.P., Boschetti, L., Justice, C.O. & Ju, J. (2008) The collection 5 MODIS burned area product - Global evaluation by comparison with the MODIS active fire product. Remote Sensing of Environment, 112, 3690–3707.

Sorice, M. G., Kreuter, U. P., Wilcox, B. P. & Fox III, W. E. (2012) Classifying land-ownership motivations in central, Texas, USA: a first step in understanding drivers of large-scale land cover change. Journal of Arid Environments, 80, 56-64.

Stephenson, N.L. (1990) Climatic control of vegetation distribution: the role of the water balance. The American Naturalist, 135, 649–670.

Syphard, A.D., Radeloff, V.C., Keeley, J.E., Hawbaker, T.J., Clayton, M.K., Stewart, S.I. & Hammer R.B. (2007) Human influence on California fire regimes. Ecological Applications, 17, 1388–1402.

Teague, W. R., Ansley, R. J., Kreuter, U. P., Pinchak, W. E. & McGrann, J. M. (2001) Economics

of managing mesquite in north Texas: a sensitivity analysis. Rangeland Ecology & Management/Journal of Range Management Archives, 54, 553-560.

Tummuri, S. & Loucks, E. (2012) Assessment of climate models for water planning applications. In: World Environmental and Water Resources Congress 2012: Crossing Boundaries (ed. by E.D. Loucks), pp. 3331-3340. American Society of Civil Engineers, Reston, VA.

Turner, D., Ostendorf, B. & Lewis, M. (2008) An introduction to patterns of fire in arid and semi-arid Australia, 1998-2004. The Rangeland Journal, 30, 95. doi: 10.1071/RJ07039

Twidwell, D., Rogers, W.E., Fuhlendorf, S.D., Wonkka, C.L., Engle, D.M., Weir, J.R., Kreuter, U.P. & Taylor, C.A. (2013) The rising Great Plains fire campaign: citizens' response to woody plant encroachment. Frontiers in Ecology and the Environment, 11, e64--e71.

USGS (2011) National Landcover Database. Available at https://data.nal.usda.gov/dataset/national-land-cover-database-2011-nlcd-2011.

USGS (2017) National Elevation Dataset. Available at https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map.

USGS (2017) Municipal Boundaries Dataset. Available at https://www.usgs.gov/core-science-systems/national-geospatial-program/boundaries-governmental-units.

USGS (2017) North American Roads Atlas. Available at https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-maps-national-atlas?qt-science_center_objects=0#qt-science_center_objects.

Vallejo, V.R., Smanis, A., Chirino, E., Fuentes, D., Valdecantos, A. & Vilagrosa, A. (2012) Perspectives in dryland restoration: approaches for climate change adaptation. New Forests 43, 561–579.

Wang, H.H., Wonkka, C.L., Grant, W.E. & Rogers, W.E. (2016) Range expansion of invasive shrubs: implication for crown fire risk in forestlands of the southern USA. AoB Plants, 8. doi:10.1093/aobpla/plw012

Westerling, A.L., Hidalgo, H.G., Cayan, D.R. & Swetnam, T.W. (2006) Warming and earlier spring increase western US forest wildfire activity. Science, 313, 940–943.

Xian, G. & Homer, C. (2009) Monitoring urban land cover change by updating the national land cover database impervious surface products. 2009 Joint Urban Remote Sensing Event, IEEE, 1-5.

Young, A.M., Higuera, P.E., Duffy, P.A. & Hu, F.S. (2016) Climatic thresholds shape northern high-latitude fire regimes and imply vulnerability to future climate change. Ecography, 40, 606–617.

Zou, C.B., Twidwell, D., Bielski, et al. (2018) Impact of eastern redcedar proliferation on water resources in the Great Plains USA—current state of knowledge. Water, 10, 1768. doi.org/10.3390/w10121768.

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