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Vegetation—Rainfall interactions reveal how climate variability and climate change alter spatial patterns of wildland fire probability on Big Island, Hawaii

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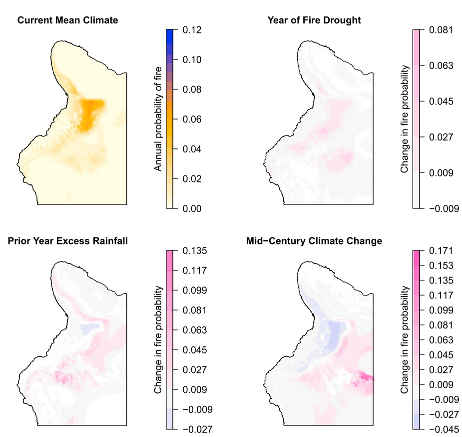
HIGHLIGHTS

- Fire is a key threat in Hawaii and other islands but predictive tools are limited.
- Spatial fire occurrence models reveal the relative influence of multiple drivers.
- Rainfall-vegetation interactions were a key predictor of fire risk variability.
- Future drying with climate change will shift peak fire risk to higher elevation.
- Fire probability will decline by populated areas but increase near high value forest areas.

GRAPHICAL ABSTRACT



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ABSTRACT

The area burned annually by wildland fire in Hawaii has increased fourfold in recent decades. The archipelago's novel fuel types and climatic heterogeneity pose significant challenges for fire risk assessment and fire management. Probability-based fire occurrence models using historical wildfire records provide a means to assess and attribute fire risk in regions of the world like Hawaii where investment in fire science is limited. This research used generalized additive models to 1) assess the relative contribution of vegetation, climate, and human-caused ignitions to the probability of fire in the northwest quadrant of Hawaii Island and 2) compare how landscape flammability varies due to interannual rainfall variability versus projected changes in mean annual rainfall (MAR) and temperature. Annual fire probability was highest for grasslands and peaked at drier conditions (0.04 at 450 mm MAR) when compared with shrublands (0.03 at 650 mm MAR) and forest (0.015 at 600 mm MAR). Excess rainfall the year prior to fire occurrence increased fire risk across grasslands, and thus overall fire probability, more so than drought the year that fire occurred. Drying and warming trends for the region under projected climate change increased maximum values of fire probability by as much as 375% and shifted areas of peak landscape flammability to higher elevation. Model predictions under future climate also indicate the largest changes in landscape flammability will happen by mid-Century. The influence of antecedent wet years on fire risk can improve near-term predictions of fire risk in Hawaii while climate projections indicate that fire management will need to be prioritized at upper elevations where high value natural resources are concentrated.

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1. Introduction

Wildland fire varies in frequency and intensity across landscapes due to the influence of climate, vegetation, and patterns of ignition (Bowman et al., 2009; Parisien and Moritz, 2009; Pausas and Keeley, 2009). Research on pyrogeography has discerned patterns in fire disturbance across geographic space from local to global scales (Bowman et al., 2014; Krawchuk et al., 2009; Murphy et al., 2013; Trauernicht et al., 2015a). These same relationships inform models of landscape flammability that integrate various predictors such as available moisture and temperature (Guyette et al., 2012; Hoyos et al., 2017), plant community structure and physiognomy (Fraser et al., 2016; Paritsis et al., 2013) as well as topography and substrate (Stambaugh and Guyette, 2008; Wood et al., 2011). These analyses contribute to both theoretical and applied aspects fire ecology. Fire-vegetation feedbacks, for instance, provide key insight into the stability and distribution of forest and savanna ecosystems (Bond and Keeley, 2005; D'Antonio and Vitousek, 1992; Murphy and Bowman, 2012; Nowacki and Abrams, 2008). Climatic thresholds of fire occurrence also help land managers and landowners identify and implement ecologically beneficial fire regimes (Schmidt et al., 2018; Twidwell et al., 2016). Landscape flammability is also relevant to understanding the risk posed by fire to valued assets and resources (Penman et al., 2014; Sturtevant et al., 2009).

By contrast, tools for wildland fire risk assessment typically draw on highly sophisticated fire behavior models in a spatially explicit framework that predict fire spread across a landscape (Ager et al., 2011; Perry, 1998; Sullivan, 2009). Fire spread models provide invaluable tools for both risk assessment and fire suppression efforts. However, in many parts of the world, limited resources and fire science capacity place real constraints on the development and validation of fire behavior models. This is especially the case on islands where novel fuels types – both endemic vegetation and completely novel, nonnative ecosystems –limit the accuracy of existing models (Beavers et al., 1999; Benoit et al., 2009; Pierce et al., 2014). In these cases, probabilistic approaches to modeling fire occurrence that use observed burned areas or historical fire records may reduce the number of assumptions underlying more complex fire spread models (Brillinger et al., 2006; Preisler et al., 2004). Applications of this approach range from stand level burn patterns based on vegetation and microclimatic factors (Gonzáles et al., 2006; Trauernicht et al., 2012) to regional analyses that integrate fire records, climate, weather, and land cover data (Dickson et al., 2006; Hoyos et al., 2017; Parisien and Moritz, 2009; Paritsis et al., 2013). A further advantage is that probabilistic approaches often allow models of fire occurrence to be parameterized from existing datasets (Bremer et al., 2018; Preisler et al., 2004).

Hawaii and other Pacific Islands provide some of the clearest evidence of both historical and contemporary fire-driven shifts from forest to savanna vegetation due to anthropogenic fire (Dodson and Intoh, 1999; Ellsworth et al., 2014; Perry et al., 2012; Trauernicht et al., 2015b). These derived savannas (sensu Veldman and Putz, 2011) appear to represent highly resilient, alternative ecosystem states (Tepley et al., 2018; Yelenik and D'Antonio, 2013) and support high frequency fire regimes compared to relatively infrequent fires in native ecosystems prior to human arrival (Athens and Ward, 2004; Burney and Burney, 2003; Perry et al., 2012). The extent of area burned annually in Hawaii has increased four-fold in recent decades, rivaling the western US in terms of the percentage of land area affected annually (Trauernicht et al., 2015b). This change in fire regime is driven by strong rain shadows, episodic drought, and frequent human-caused ignitions, combined with agricultural abandonment which has left large-scale, continuous beds of fine fuels covering a third of the archipelago's undeveloped land surface (c. 4000 km^2; Hawbaker et al., 2017). With lightning strikes relatively rare on oceanic islands and prescribed or managed burning largely ceasing in Hawaii with the closure of large-scale sugarcane plantations in the past decade, the vast majority of fires are caused by humans either accidentally or as arson (Trauernicht et al., 2015b). Although >80% of the area burned annually in Hawaii is constrained to nonnative, derived savannas (Hawbaker et al., 2017), the novel fire regime exposes both residential areas and forested ecosystems to fire impacts. Native ecosystems in Hawaii are particularly sensitive in that fire disturbance typically favors nonnative species establishment leading to native species and habitat loss and long-term conversion to more fire-prone vegetation (Ainsworth and Kauffman, 2013; D'Antonio et al., 2017; LaRosa et al., 2008; Trauernicht et al., 2018).

Despite plot- and site-level evidence of increasing flammability in Hawaii (Ainsworth and Kauffman, 2013; D'Antonio et al., 2011, 2017; Hughes et al., 1991), few studies examine how savanna expansion alters the spatial patterns of fire for island landscapes (D'Antonio et al., 2000; Ellsworth et al., 2014; Perry and Enright, 2002), nor how fire occurrence may be modulated by spatial and temporal climate variability (Chu et al., 2002; Dolling et al., 2005; Van Beusekom et al., 2018). In Hawaii, this is due, in part, to limited investment in fire research and risk assessment tools relative to the continental US as well as sparse weather data relative to the islands' radical climate variability (Weise et al., 2010). As elsewhere in the tropics, Hawaii also presents challenges in terms of predicting future changes in landscape flammability. Locally downscaled climate projections are largely boiled down to mean annual variables, such as temperature and rainfall, whereas fire risk is more influenced by the extremes, or tails, in the distribution of these conditions. In temperate ecosystems, future fire occurrence is linked to increasing duration of the fire season, or the hotter, drier climatic conditions under which fire is most likely, under warming temperatures (Jolly et al., 2015; Moritz et al., 2012; Westerling et al., 2006). In contrast, understanding shifts in fire activity due to climate change in the tropics is constrained both by the lack of research establishing climatic and weather thresholds for fire occurrence as well as the limited ability of climate models to capture changes in the El Niño-Southern Oscillation and rainfall seasonality such as the Asian Monsoon (Huang et al., 2013; Turner and Annamalai, 2012; Vecchi and Wittenberg, 2010), which are strong drivers of variation in tropical fire regimes (Chu et al., 2002; Gill et al., 2000; Van Der Werf et al., 2008). Coarser climatic variables like mean annual rainfall may still constrain and promote fire activity, creating climatic 'sweet spots' for fire (Bradstock, 2010; Murphy et al., 2011). Therefore, examining the relative influence of climate variability and average climatic conditions on fire occurrence remains a key task for understanding how landscape flammability varies in the tropics.

In response to the limited availability of landscape-scale analyses of fire occurrence and direct requests from land managers and ecosystem service modelers for improved assessments of fire risk in Hawaii, a modeling framework was developed that draws on fundamental fire regime concepts (i.e., pyrogeography; Krawchuk et al., 2009; Bowman et al., 2014) and existing data sets to model the probability of fire occurrence across a large (3000 km^2) landscape encompassing the northwest quadrant of the 'Big Island' of Hawaii. The research objectives were: 1) to develop a model of fire occurrence to assess the relative contribution of vegetation, climate, and ignitions to the probability of fire for the region; and 2) compare how landscape flammability varies due to interannual rainfall variability vs. longer-term projected changes in mean annual rainfall and temperature.

2. Materials and methods

2.1. Study region

We selected the northwest quadrant of Hawaii Island (a.k.a. "Big Island") for this analysis primarily because it provides the longest history of wildland fire burned area records (i.e., fire scar maps) for the state of Hawaii (Castillo et al., 2003). The region also contains watersheds of interest in two related, interdisciplinary assessments of biophysical, economic and cultural landscape values (Bremer et al., 2018; Wada et al., 2017). The study area is a c. 3000 km^2 island landscape with dramatic ranges in climate, geology and ecology. Situated on the western flanks of Kohala, Hualalai and the saddle between Mauna Kea and Mauna Loa volcanoes, elevation ranges from 0 to 3180 m above sea level (Fig. 1a). Mean annual rainfall ranges from 200 mm towards the coast to >3000 mm in higher elevation areas receiving orographic rainfall (Fig. 1b). Historical rainfall indicates a significant drying trend for west Hawaii Island over the past several decades (Frazier and Giambelluca, 2016) and, although downscaled climate projections are spatially variable, they predict 18–25% declines in annual for drier areas of the region by mid-century, in addition to warming temperatures (Elison Timm, 2017; Giambelluca et al., 2008; Elison Timm et al., 2015).

Most of Hawaii's landscape has been heavily transformed by historical land use and species introductions (Vitousek et al., 1987). Fire frequency likely increased with initial human settlement and there are anecdotal accounts of Hawaiians using fire to clear agricultural lands as well as larger scale burning to manage pili (*Heteropogon contortus*) grasslands for thatch and fernlands for food/fodder (Kirch, 1982; McEldowney, 1979; Menzies, 1920). After European contact, disease, economic integration and colonial land privatization in the interests of agricultural development led to dramatic increases in the human ecological footprint in Hawaii. In west Hawaii Island, cattle became the dominant land use beginning in the 19th Century and, despite declines through the late 20th Century, ranching remains a central part of local culture and livelihoods (Bremer et al., 2018). The early expansion of the cattle industry reduced forest cover (Blackmore and Vitousek, 2000) but, at present, unmanaged feral ungulates and the spread of nonnative plant species, especially fire-adapted grasses, arguably pose the greatest land management and conservation challenges across the archipelago (Mueller-Dombois and Spatz, 1975; Vitousek et al., 1987; Wehr et al., 2018). Increases in the extent of large fires in recent decades coincide with dramatic declines in the extent of actively grazed lands and plantation agriculture beginning in the 1960s (Gollin and Trauernicht, 2018; Trauernicht et al., 2015b).

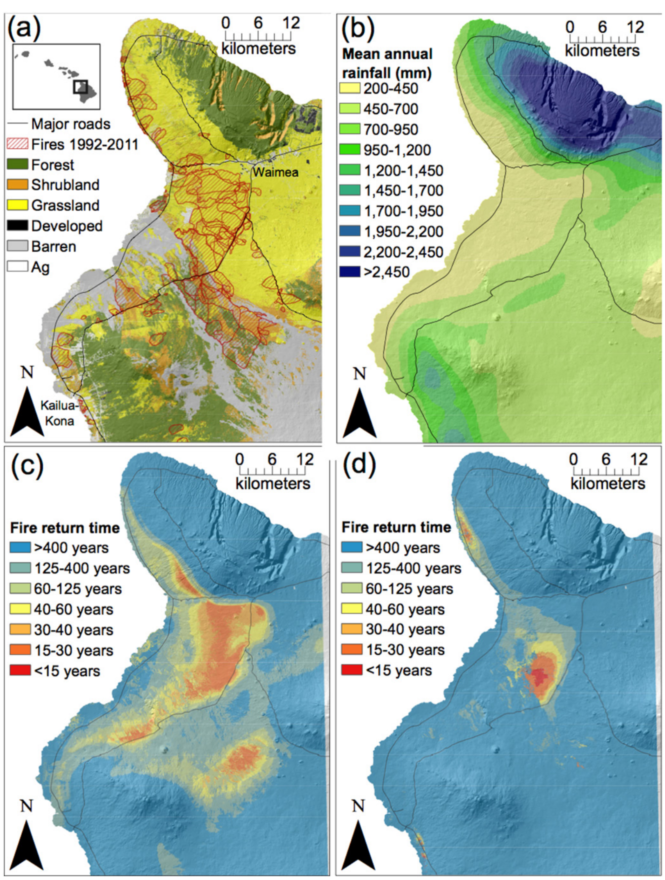

Fig. 1. Maps of study region indicating (a) land cover and fire history, (b) mean annual rainfall, and landscape flammability predictions based on generalized additive models parameterized (c) without a spatial predictor term and (d) with a spatial predictor term (see Methods). Values of landscape flammability are presented as fire return intervals, derived from the reciprocal of the probability of annual fire occurrence.

Grassland is the most extensive vegetation type in the study region, covering c. 1000 km^2, of which 95% is dominated by the nonnative species *Pennisetum setaceum* at lower elevation and *Pennisestum clandestinum* at moist, middle elevations (Blackmore and Vitousek, 2000). Shrublands cover c. 340 km^2, of which 67% are classified as native species dominated. Much of these shrublands, however, contain a significant nonnative grass component and are interspersed with the contiguous nonnative grasslands. The largest recorded fires in Hawaii (10–18,000 ha) have occurred in these nonnative grasslands and shrublands in the study region. Forest covers c. 830 km^2 across a wide elevation gradient up to 2500 m. Native forest (62% of total forest cover) includes wet, mesic and dry types, which are typically confined to middle to upper elevation areas. The region contains the largest remaining tracts of Hawaii's most diverse and threatened tropical forests (Pau et al., 2009) which adjoin nonnative grasslands and shrublands. Another 630 km^2 of land consists of barren or sparsely vegetated lava flows which are increasingly covered in nonnative grass and capable of carrying fire (Gollin and Trauernicht, 2018). Human population density is low relative to other islands in the archipelago, with only 120 km^2 of developed areas and 13 km^2 of agriculture cover. Fires are most frequently started accidentally by people along roadsides (Pierce and Pickett, 2014) and suspected arson is not uncommon. Although lightning is far less frequent on islands than continental regions, several recent large fires have been ignited by lightning in the study region.

2.2. Modeling flammability

Landscape flammability was derived from a 20-year (1992–2011) dataset of 91 fire perimeters (ranging from <10 to >10,000 ha) for the NW quadrant of Hawaii Island, mapped by the Hawaii Wildfire Management Organization and the USGS Monitoring Trends in Burn Severity program (Hawbaker et al., 2017). Using R software, polygons of annual area burned were converted to gridded rasters at 30 × 30 m resolution to align with the 2012 LANDFIRE Existing Vegetation Type product for Hawaii. The response variable, annual fire probability, was derived by randomly selecting 1000, 30 × 30 m grid cells from the 3.36 million-cell landscape from each year of the fire history and classifying each as burnt or unburnt (a binomial response) for a total of 20,000 sample points. Each sample point was also attributed with the following predictor variables: (i) simplified land cover (Forest, Shrubland, Grassland, Agricultural, Developed, and Other from LANDFIRE; Rollins, 2009); (ii) ignition density derived from point-based wildfire ignition records from 2004 to 2012 (Pierce and Pickett, 2014); (iii) mean annual rainfall; (iv) rainfall anomaly the year of the fire, (v) rainfall anomaly the year prior to the fire; and (vi) mean annual temperature (mean annual climate variables: Giambelluca et al., 2013; annual rainfall: Frazier and Giambelluca, 2016).

Generalized additive models (GAMS; e.g. Chou et al., 1993; Preisler et al., 2004; Wood, 2006) were used to fit the probability of fire occurrence as a function of all possible combinations of predictor variables. Interactions between land cover and each rainfall predictor (3 interactions total) were analyzed because mean annual rainfall is a key ecological criterion by which vegetation types are classified (e.g., dry, mesic, and wet forest) and because rainfall anomalies were expected to affect fire risk differently in grassland, shrubland, and forest. For example, fire probability may increase in both grasslands and forest under drought, but wet years might only affect fire probability in grasslands through biomass accumulation (Govender et al., 2006; Greenville et al., 2009). Fire probability would likely differ in its response to daily and seasonal fluctuations in temperature across vegetation types, however, an interaction between mean annual temperature and land cover was not expected and therefore not modeled. Ignition densities are highest in developed areas and grasslands (Trauernicht et al., 2015a, b) but are so comparably low across forested areas that the interaction between ignition density and land cover was not included. A total of 140 models were ranked relative to the null model using Akaike's Information Criterion (Burnham and Anderson, 2002).

This approach is effectively a habitat distribution model of flammability, a concept that has been applied by others to examine the drivers fire occurrence across multiple spatial scales (Hoyos et al., 2017; Parisien and Moritz, 2009; Paritsis et al., 2013). In this analysis, the use of randomized, annual samples was intended to equate model predictions to the annual probability of fire occurrence per grid cell. Quantifying annual fire probability for an entire landscape can be alternatively interpreted as regional fire frequency (sensu Li, 2002) or fire return interval (i.e., the reciprocal of annual probability). Thus, the response variable may be best interpreted as how the vegetation and climatic features in the landscape support low or high frequency fire regimes. Some degree of autocorrelation was expected in the analysis over both spatial (e.g., multiple points sampled from single fires) and temporal (e.g., adjacent or identical locations sampled year to year) dimensions. Restricting annual samples to 1000 random pixels (<0.003% of the 3000 km^2 landscape) was intended to minimize autocorrelation and model overfitting. Temporal autocorrelation was also addressed by including a random effect for year (Brillinger et al., 2006). To explore spatial autocorrelation, we ran a Moran's I correlogram (ncf package in R) of residuals from the initial model set. We also fit another model set with the same predictors above (i.e., 140 model combinations) in addition to a spatial, or geographic, predictor (e.g. "+ s(x,y)") to account for spatial autocorrelation (Simpson, 2012). We present and compare both model sets to better understand the predictive behavior of GAMs for this application.

2.3. Spatial predictions

The Raster package in R (Hijmans et al., 2012) and the best supported GAMs were used to predict the annual probability of fire occurrence across the study region under current land cover and mean climate conditions (i.e., annual rainfall anomalies set to zero). Standard deviations (SD) of annual rainfall per grid cell from the 21-year (1991–2011) rainfall history were used to examine the effects of positive (+1 SD) and negative (−1 SD) rainfall anomalies for both the year of fire and the year prior to fire on predicted landscape flammability (a total of four scenarios). The effects of climate change on landscape flammability was assessed by running model predictions with future mean annual rainfall and temperature under the RCP 8.5 climate scenario (IPCC) available from two downscaled data sets for Hawaii. Statistically downscaled projections were available for both mid-Century (2040–2060) and late Century (2080–2100; Elison Timm et al., 2015 and dynamically downscaled projections were available for late Century (Zhang et al., 2017), providing three future climate scenarios: (i) Mid-century RCP 8.5 Statistical; (ii) Late Century RCP 8.5 Statistical; and (iii) Late century RCP 8.5 Dynamical. Projected dynamical variables were produced by adding the difference between future and present modeled values to the current values derived from spatially interpolated weather observations (Giambelluca et al., 2013). The convention among climate impact modelers in Hawaii to account for differences between the statistical and dynamical projections is to present and compare results using both sets of projections (L. Fortini, pers. comm.). To compare current, mean conditions with the effects of annual rainfall anomalies and future climate, the standard error (SE) of model predictions for each grid cell was determined by bootstrapping randomized burned area sampling, model fitting, and model prediction 100 times each for all scenarios (at 250 × 250 m resolution to reduce processing time). Statistically significant change in flammability was defined as any area for which there was no overlap in the 95% confidence intervals ($\pm SE * 1.96$) between predictions for mean, current conditions and each of the climate scenarios. Change in landscape flammability was examined by plotting rasters and boxplots of the difference in fire probability between current, mean fire conditions and each of the scenarios for all grid cells with a statistically significant change. In addition, density scatter plots of flammability values versus elevation were examined for each scenario.

3. Results

3.1. Fire occurrence and model results

Of the dominant, simplified land cover classes, "Grassland", "Shrubland", "Forest" accounted for 51%, 21%, and 18%, respectively, of the area burned across the landscape (Fig. 1a). The percent of the total area burned across grasslands and shrublands was disproportionate to their spatial extent. Grasslands, which cover one-third of the study area, accounted for 51% of the total area burned. Shrublands comprised just over 10% of land cover and accounted for 21% of the area burned. Forests comprised 27% of land cover and accounted for 18% of the area burned. For the fire occurrence models, the global models were best supported among both the initial set of GAMs (Akaike Weight > 0.99) and the set of GAMs with the spatial predictor (Akaike Weight > 0.99). Correlograms indicated some degree of spatial autocorrelation in the residuals of the model without the spatial predictor (Supplemental), indicating lower confidence in model error estimates. However, the explained deviance for both model sets showed little variability over 100 replicated model runs (46.3% ± 0.003 SE with spatial term vs. 34.7% ± 0.003 SE without spatial term).

3.2. Effects of predictors

Effects plots of individual predictors indicate that the GAM components provide good fits to the data (Fig. 2). Since the GAM additively combines the effects of predictor variables, the relationships between fire probability and the predictors presented are the same whether or not the spatial term is included in the global model (Wood, 2006). Mean annual rainfall (MAR) illustrates different climatic 'sweet spots' for fire occurrence in grasslands, shrublands, and forest across the rainfall gradient (Fig. 2b). Fire probability was highest for grasslands and peaked at drier conditions (0.04 at 450 mm MAR) when compared with shrublands (0.03 at 650 mm MAR) and forest (0.015 at 600 mm MAR). Rainfall anomalies the year prior to fire exerted a strong effect on grasslands in which wetter conditions (positive anomalies) resulted in much higher fire probability and drier conditions (negative anomalies) slightly increased fire probability in forests and shrublands (Fig. 2c). Drier conditions (negative anomalies) the year of fire increased fire probability for both forests and shrubland vegetation types with the largest effect in shrublands, whereas fire probability in grasslands was highest with no rainfall anomaly (Fig. 2d). Wetter conditions the year of fire (positive anomalies) resulted in a slight decrease in fire probability across vegetation types relative to normal conditions (Fig. 2d). There were two peaks in fire probability for mean annual temperature (Fig. 2e) and a single peak in fire probability at intermediate values of ignition density (Fig. 2f). Among the predictors, the interaction between land cover and prior year rainfall anomaly explained the largest proportion of all model predictors (14.2%), followed by the interaction between land cover and mean annual rainfall (10.5%), the interaction between land cover and rainfall anomaly the year of fire (10%), mean annual temperature (7%), and ignition density (3%).

3.3. Landscape flammability predictions without the spatial term

The GAM without the spatial term predicted a 'belt' of peak fire probability across the middle to low elevations of the landscape under current, mean climate conditions, largely associated with the extensive

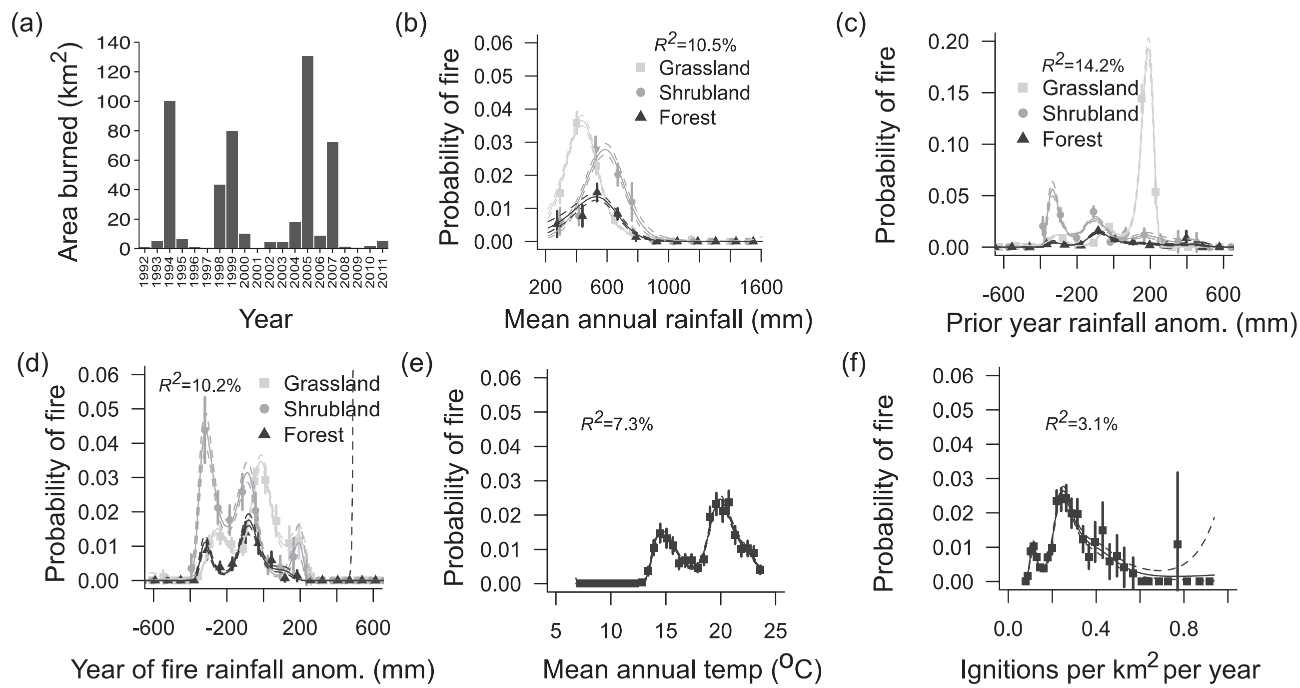

Fig. 2. Plots of (a) annual area burned across the study region and (b–f) the effects of individual predictors used in the generalized additive models (GAM). Points and error bars represent the mean and 95% confidence intervals, respectively, of observed fire probabilities binned across the independent variables. Solid lines are GAM predictions, dashed lines are the 95% confidence intervals, and R^2 values are the deviance explained by individual GAMs fitted with the indicated predictors.

grasslands of the region (Fig. 1c). Another peak in flammability distribution coincided with higher elevation areas comprised of mixed shrubland and forest that are drier due to the trade wind inversion layer (1800–2400 m) and the rain shadow of Mauna Kea (Fig. 1b, c). There was an increase in fire probability under drier conditions the year of fire, largely within the same area of peak flammability under mean climate conditions (Fig. 3a,b). Wet conditions the year of fire produced relatively little change in fire probability (Fig. 3c,d). Drier conditions the year prior to fire reduced fire probability across much of the grassland area in the center of the study region, but increased fire probability in the upper elevation areas with greater shrubland and forest cover (Fig. 3e,f). Wet conditions the year prior to fire resulted in the largest increase in maximum fire probability and across a wider extent of the landscape than current, mean conditions (Fig. 3g,h).

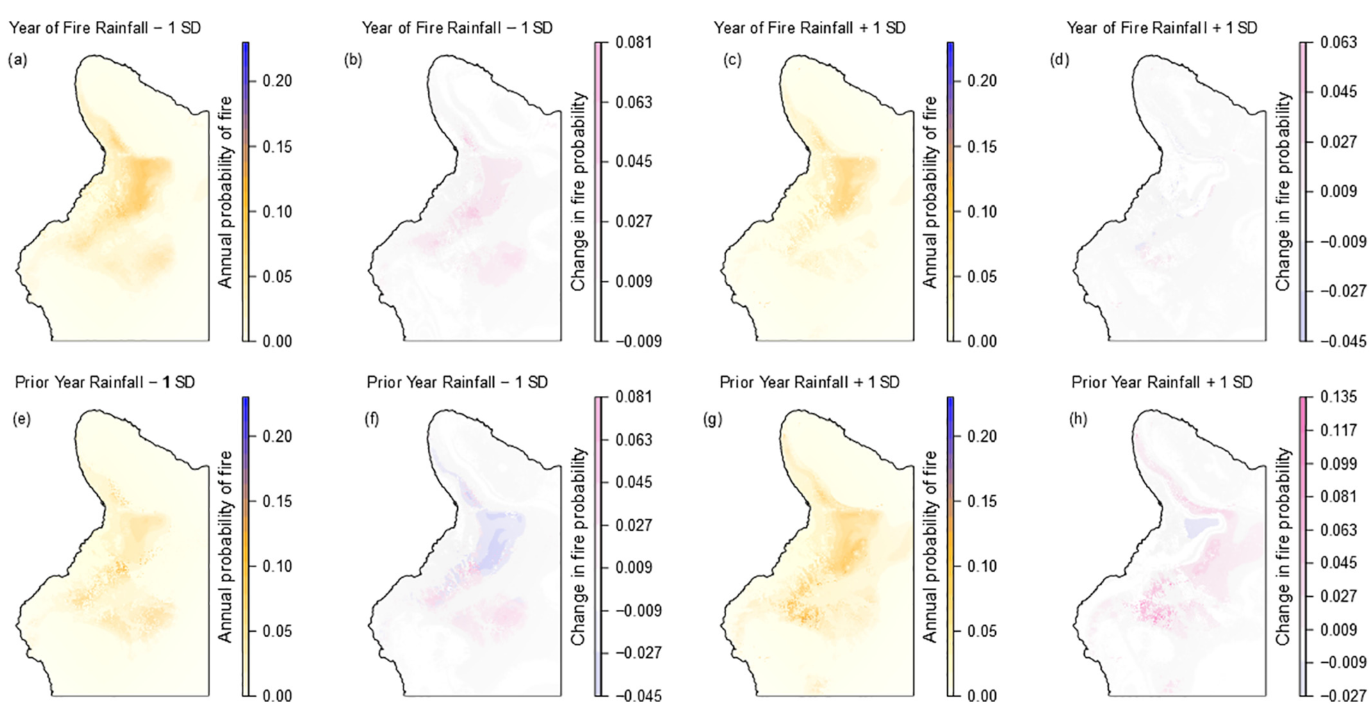

Fig. 3. Effects of annual rainfall anomalies on predicted landscape flammability and the change in fire probability relative to mean, current conditions under (a,b) negative anomaly the year that fire occurs, (c,d) positive anomaly the year that fire occurs, (e,f) negative anomaly the year prior to fire and (g,h) positive anomalies the year prior to fire. Anomalies were determined as plus or minus one standard deviation determined per grid cell from a 21-year (1990–2011) annual, cumulative rainfall history. Gray shading indicates areas of nonsignificant change, where the 95% confidence intervals of bootstrapped predictions overlap between each scenario and current, mean conditions.

Landscape flammability increased under all three future climate scenarios in terms of median and maximum predicted fire probability and resulted in a spatial shift in peak flammability over the landscape. In general, projected decreases in rainfall and increases in temperature resulted in an inland (eastward) shift in peak flammability, with fire probability decreasing at lower elevation sites and increasing at higher elevation sites (Fig. 4). The change in landscape flammability from current, mean conditions to mid-Century climatic conditions was greater than the change from mid-Century to late Century (Fig. 4c–h). The distributions of change in fire probability per grid cell indicated that the magnitude of the increased fire probability under a wet year prior to fire occurrence is comparable to projected future conditions (Fig. 5). Maximum change in fire probabilities were greater under the future scenarios, but the median change was greater under a wet year prior to fire. Plotting fire probability against elevation for all scenarios illustrated that future conditions are characterized by a larger increase in fire probability at higher elevations than under current rainfall anomalies (Fig. 6).

3.4. Landscape flammability predictions with the spatial term

In contrast to the results above, the GAM with the spatial term predicted fire probabilities that were heavily weighted towards the most frequently burned area of the landscape (Fig. 1a,d). The directional effects of rainfall anomalies on fire probability were similar to predictions without the spatial term, however, areas of increased flammability showed little spatial change and were centered over the areas of maximum flammability predicted for current, mean conditions (Fig. S2, Appendix). Predictions for future climate scenarios were similarly constrained in space, but also resulted in fire probabilities far greater than conditions under mean, current climate (Fig. S1, Appendix). Maximum predicted values under climate change scenarios, for example, approached 100% for the annual probability of fire occurrence, an increase by three- to fourfold over maximum fire probabilities under current, mean conditions (Fig. S3).

4. Discussion

4.1. Fire probability vs. landscape flammability

This analysis essentially uses historical fires as a signal to assess and attribute flammability over ecological and climatic space. The modeling approach and available data impose some constraints on both the interpretation and attribution of landscape flammability. First, the twenty-year fire history is a relatively short-term data set for fire regimes, but was purposefully limited so as not to be confounded by changes in land use, especially ranching and grazing regimes, that would not have been accounted for by the land cover data. Second, the use of fire probability, a binary response, indicates relative fire frequency but not intensity, which is another key characteristic of fire regimes. Third, the older fire perimeters (1992–2001) were only attributed with year of occurrence, constraining the temporal resolution of the climatic predictors to annual time steps. Finally, the available land cover and ignition density data sets were fixed in time which prevented the model from accounting for fire-driven or other vegetation change and temporal variability in human-caused ignitions. However, in light of these limitations, the deviance explained by the best supported models (34.7% and 46.3%) exceeded expectations. In other words, despite missing finer-scale variability in weather conditions and the limitations in accounting for human influence on both ignition sources and fire suppression effects, a relatively simple set of predictors (vegetation, climate, and ignition density) explained a good proportion of the variance in observed fire probability. In addition, despite relatively coarse climate data (i.e., annual and future mean change), the facility with which the GAM framework provided numerical and spatial predictions when these parameters were altered for the various scenarios revealed both anticipated and novel results. The model outcomes will be discussed below in the context of fire regimes ultimately to make the case for the advantages to this approach in that it: 1) is employable with existing, regionally accessible data; 2) presents transparent assumptions that simplify the assessment and communication of fire risk; and 3) points clearly towards opportunities to improve model performance.

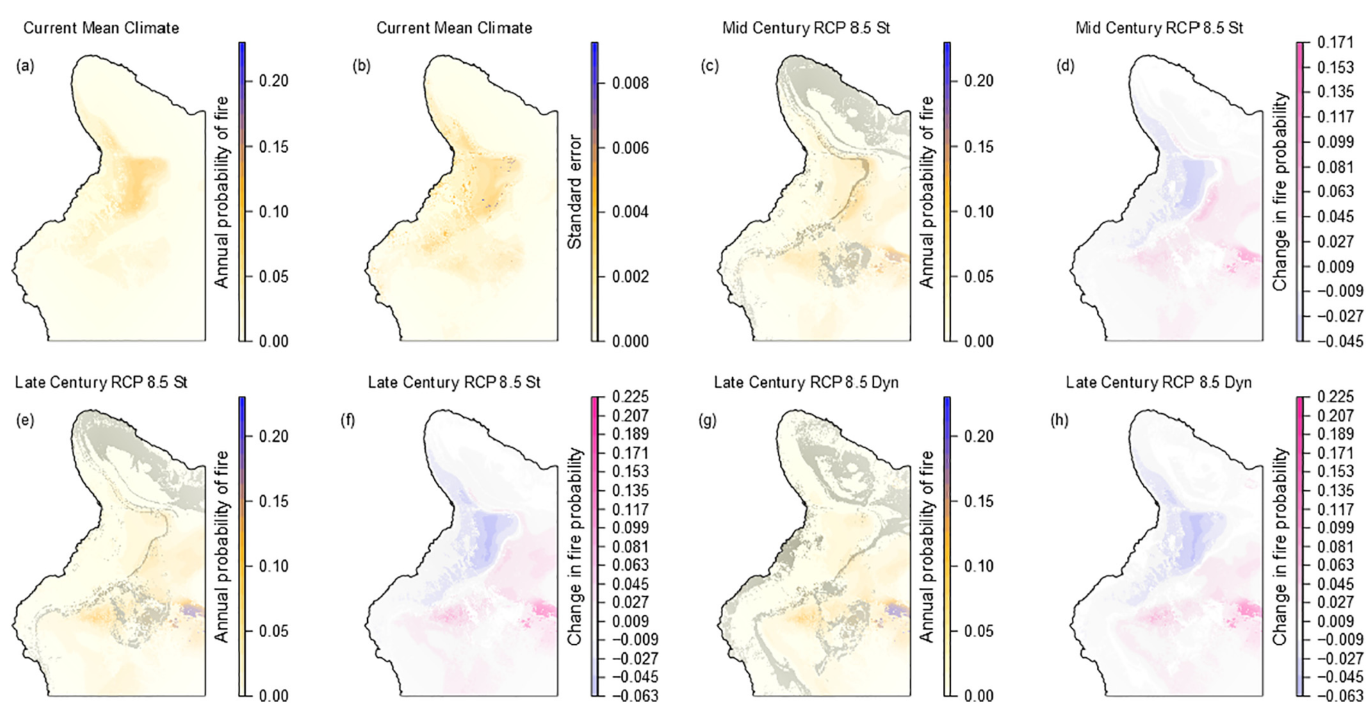

Fig. 4. Landscape flammability (a) prediction and (b) standard error under mean, current climate conditions and predicted landscape flammability and change from mean, current condition under future mean annual temperature and rainfall projections for (c,d) statistically downscaled mid-Century (2040–2060) RCP 8.5 scenario, (e,f) statistically downscaled late-Century (2080–2099) RCP 8.5 scenario, and (g,h) dynamically downscaled late-Century RCP 8.5 scenario. Gray shading indicates areas of nonsignificant change, where the 95% confidence intervals of bootstrapped predictions overlap between each scenario and current, mean conditions.

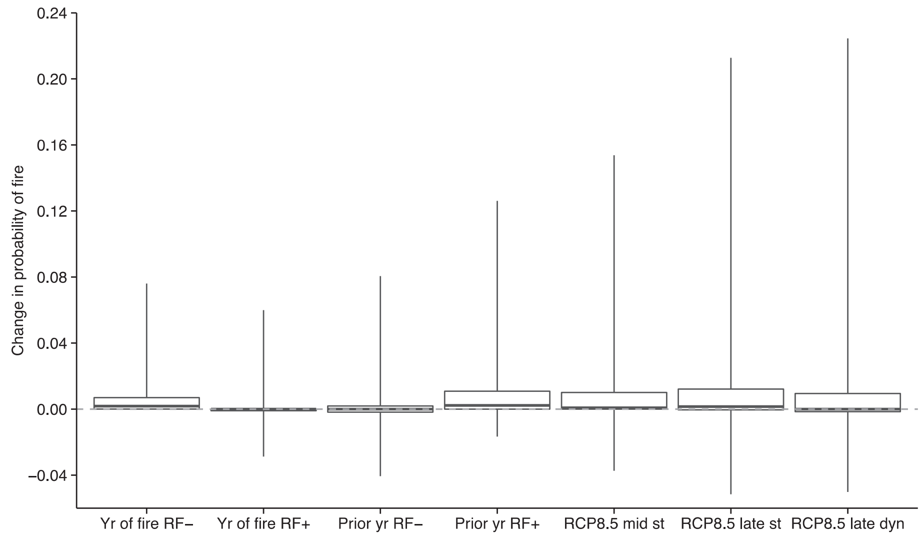

Fig. 5. The distributions of per grid cell change in fire probability values between mean, current conditions and each of the annual rainfall anomalies and future climate scenarios using the Generalized Additive Model without the spatial predictor term. Whiskers indicate minimum and maximum values, boxes indicate 25th and 75th percentiles, and the horizontal line indicates the median.

The first objective of this research was not to strictly predict fire probability, or where fires are most frequent in the study region (Fig. 1a), but to assess how climate and vegetation contribute to landscape flammability, defined here as the relative propensity for areas or ecosystems across the landscape to burn. The GAMs used in this analysis allow one to partition the variance explained across model components such that we can examine relative contribution of the predictors. This includes understanding the effects of using geographic location as a predictor variable. The spatial term increased the total deviance explained by the model by c. 11%, however, it is ultimately intended to account for issues of spatial autocorrelation which may emerge from drawing multiple grid cells from the same or spatially clustered fires. Model predictions with the spatial term provide a good indication of where historical fires have been most frequent (e.g., Fig. 1a, d), but do little to indicate how the other predictor variables contribute to fire risk across the landscape (Fig. 2). In other words, the effect of the spatial term on fire probability is strong enough that model predictions made with this term effectively conceal the effects of vegetation and climate across the larger landscape. In addition, by weighting predictions of high fire probability to the geographic space in which historical fires were most frequent, the use of the spatial term also limits the ability of the model to assess the effects of spatial changes in climate parameters on fire probability, with respect to both annual rainfall anomalies and future climate change.

Despite the inherent uncertainty around predicting future fire risk, the magnitude of change in projected climatic conditions for the study region largely lie within the range of observed climate variability captured in the model fitting. In other words, climate change will not affect the absolute values or range of climate parameters as much as it will change their spatial patterns over the landscape (Elison Timm et al., 2015). Therefore, one would expect that predicted fire probability under climate change would change more in its spatial distribution than in its magnitude. However, the GAM with the spatial term produced dramatic increases in fire probability under climate change (e.g., close to 1) that were 'centered' over the areas of highest probability predicted under current, mean climatic conditions (Fig. S2,

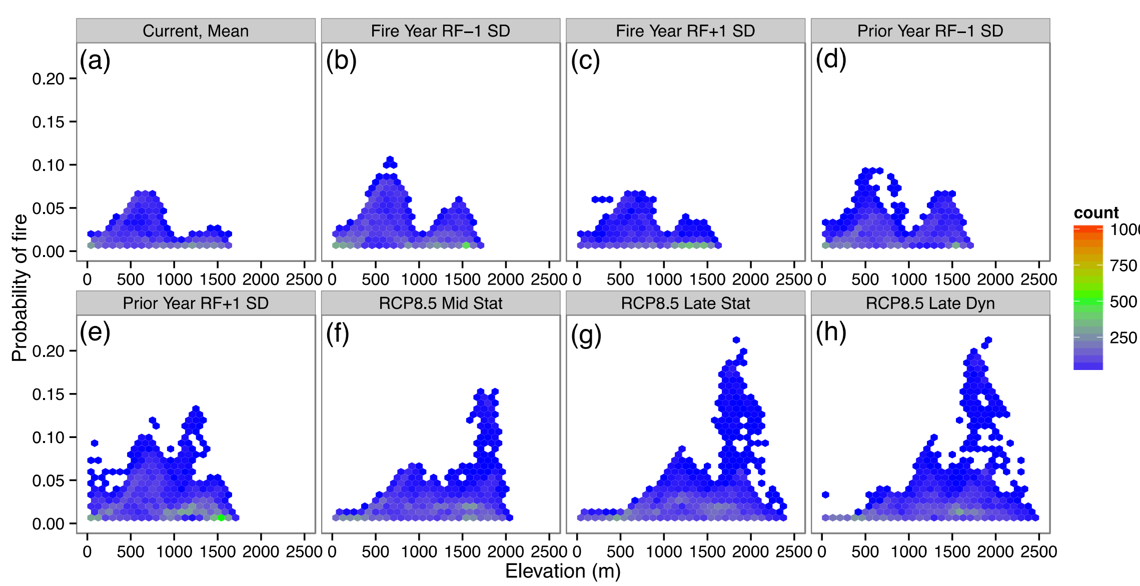

Fig. 6. Scatter plots illustrating the counts of grid cells within binned fire probability values versus elevation for current, mean conditions and each of the annual rainfall anomaly and future climate scenarios.

Appendix). This pattern reflects the tendency for the spatial term to weight fire probability towards areas where historical fires are most frequent and suggests the GAM with the spatial term poorly accounts for the potential effects of spatial changes in climate parameters on predicted fire probability. This pattern of centering predicted fire probability is also reflected in model predictions for annual rainfall anomalies using the spatial term (Figs. S1, S3, Appendix). The statistical argument whether or not to use the spatial term in this analysis may be most simply framed by concerns over potential effects of spatial autocorrelation on the error estimates of individual model predictions. First, the Moran's I correlogram indicated only a slight degree of spatial autocorrelation (Fig. S4, Appendix). Visually, the relationships between fire probability and individual predictor variables indicate that the GAM provides effective predictions relative to variance in the actual data (Fig. 2). However, it is also important to point out that the comparisons of the effect of annual and future climate variability on landscape flammability (the second research objective) depended not on the estimated error of individual models, but on the error of replicated model predictions (N = 100) derived by bootstrapping both randomized sampling of the landscape and model fitting. In summary, spatial autocorrelation is nominal and the use of the spatial term constrains both the ability to assess the effects of climate and vegetation on fire probability as well as produces highly questionable fire probability predictions under scenarios in which climate parameters are altered. Therefore, despite having a lower explained deviance, it is argued that the GAM *without* the spatial term more effectively addresses the stated research objectives and will be discussed from here forward.

4.2. Flammability across vegetation, mean climate, and ignition density

The predominance of fire in grasslands and shrublands matches previous descriptions of fire occurrence across vegetation types in Hawaii based on both fire perimeters and ignition points (Hawbaker et al., 2017; Trauernicht et al., 2015b). The differences in burned area extents are reflected in the relationship between fire probability and mean annual rainfall, in which maximum probability is highest for grasslands (Fig. 2b). Although forest fires comprise a relatively small proportion of area burned, frequent grassland fires are linked to the contraction and degradation of both native and non-native forest types in Hawaii (Ellsworth et al., 2014; LaRosa et al., 2008). The peak in fire probability along the rainfall gradient conforms to theoretical predictions that fire occurrence is constrained by limited fuels at drier sites and excess fuel moisture at wetter sites (Bradstock, 2010; Murphy et al., 2011). The differences of this relationship for grasslands, shrublands, and forests in Hawaii reflect the positive fire-vegetation feedbacks in ecosystems dominated by fine fuels (i.e., the Grass-fire Cycle; Hughes et al., 1991; D'Antonio and Vitousek, 1992) but also the negative fire feedbacks imposed by closed canopy forest (Beckage et al., 2009; Trauernicht et al., 2012, 2016). Interestingly, these results provide empirical evidence in support of a more recent hypothesis that the relationship between fire and rainfall is differentially modulated by herbaceous and woody fuels in tropical savannas (Kahiu and Hanan, 2018). Although a weaker predictor than annual rainfall variability, the different 'sweet spots' for flammability across grassland, shrubland and woody vegetation types created by the gradient in mean annual rainfall suggests that it is a key indicator of fire risk over the landscape. This relationship also lends weight to considering how projected spatial shifts in future mean annual rainfall may alter flammability in the future.

Temperature is not typically used as a predictor of fire probability in Hawaii due to its narrow range in daily and seasonal variability (Derek Wroe, National Weather Service, pers. comm.) but has been included in other analyses of fire occurrence in the tropics (Hoyos et al., 2017; Van Beusekom et al., 2018). Mean annual temperature was included in this analysis as it varies substantially across elevation in the study region, declining as elevation increases. The two peaks in fire probability along the temperature gradient (Fig) may reflect vegetation patterns as fire-prone grasslands dominates warmer, low elevation sites whereas fire-prone shrublands are found at higher elevation (Fig. 1). As with mean annual rainfall, the inclusion of mean annual temperature in the top-ranked model also justifies examining the effects of projected temperature change, which is increasing more rapidly at higher elevation (Elison Timm, 2017; Giambelluca et al., 2008), on future landscape flammability.

Although it seems counterintuitive, ignition density was not expected to be a strong predictor of fire probability. This is because 95% of all wildfire ignitions across the main Hawaii Islands (c. 1000 per year) result in fires < 4 ha (Trauernicht et al., 2015b). Therefore, the burned area perimeters used to derive fire probability in this analysis account for a small percentage of total wildfire ignitions. Ignition density was ultimately included as a predictor because it provides a human dimension to landscape flammability. Human activity is estimated to account for >98% of wildfire ignitions in Hawaii (Trauernicht et al., 2015b). As with mean annual rainfall, there is a peak in fire probability along the ignition density gradient. The lower end indicates the obvious relationship that the absence of ignitions limits fire activity. Conversely, the low fire probability at high values of ignition density likely reflects the effect of the built environment on constraining fire size in populated areas where ignition densities are actually highest (Archibald et al., 2009; Parisien et al., 2012).

4.3. Annual and future climate variability

It was expected that annual rainfall anomalies would contribute to the high variability in annual area burned in the study region. Prior research in Hawaii has linked increases in total area burned to drought (Chu et al., 2002; Dolling et al., 2005) and the National Weather Service 'Red Flag' warning for elevated fire risk in Hawaii uses the Keetch-Byram Drought Index along with relative humidity and wind speed. Dry conditions the year of fire increased fire probability in the NW Big Island by as much as 130%, with the strongest effect on shrublands, and with peak flammability largely occurring within the same geographic space as under mean climatic conditions (Fig. 3a,b). More surprising was how strongly wet conditions the year prior to fire increased fire probability in grasslands (Fig. 2c). Excess rainfall the year prior to fire increased peak fire probability as much as 225% and this increase occurred across a wider expanse of landscape (Fig. 3g,h) and into higher elevations (Fig. 6e) than under drought conditions the year of fire. That this effect is restricted to grasslands makes sense mechanistically given how responsive grass productivity, and hence fuel loading, is to rainfall (Govender et al., 2006; Greenville et al., 2009). Seasonally dry tropical savannas show similar patterns where the annual area burned is positively correlated with wet season rainfall (Gill et al., 2000; Van Der Werf et al., 2008). Interestingly, increases in annual area burned in Hawaii have been attributed to El Niño due to drought the following season (Chu et al., 2002). However, El Niño events in Hawaii are also associated with wetter than average summers prior to drought events (Trauernicht, 2015). These results indicate this phenomenon is also responsible for observed increases in the extent of wildland fire. Wildland firefighters in Hawaii qualitatively consider grassland fuel loading due to excess rain as a fire risk factor (Gollin and Trauernicht, 2018), but this relationship has not been quantified until now. Negative rainfall anomalies the year prior to fire reduced fire probability more so than wet conditions the year of fire, especially in grassland areas, suggesting fuel limitation may decrease fire risk the following year. This also aligns with firefighter reports of reduced fuels during longer term drought (Chief Eric Moller, US Army Fire and Emergency Service, pers. comm.).

Both statistically and dynamically downscaled climate projections generally agree that the NW Big Island will experience significant drying and warming in the coming decades (Elison Timm et al., 2015; Zhang et al., 2017). The resultant shift in peak flammability inland and upward in elevation under all climate scenarios (Figs. 5 and 6) has critical implications for natural resource protection in Hawaii because high value, remnant native ecosystems are more extensive at higher elevations (Friday et al., 2015). This trend is especially troubling given the positive feedback between fire and nonnative grasses and separate analyses indicating future increases in ecosystem invasibility in Hawaii, including of potential expansion of grass and shrub species known to be fuel hazards (e.g., *Melinis minutiflora* and *Leucaena leucocephala*; Vorsino et al., 2014). The extent of dry grassland and forest is projected to expand on Hawaii island under climate change but it is uncertain how or whether climate change alone will contribute to future forest conversion to more fire-prone shrublands and grasslands (Fortini et al., 2017). However, the upward shift flammability indicated by this research may accelerate future conversions and/or contraction of forest biomes in Hawaii and increase the vulnerability of remnant habitats (Fortini and Jacobi, 2018). Another key finding is that the most dramatic spatial shifts in flammability are projected to occur by middle of the 21st century. These results suggest that changes in fire risk should anticipated by planners, land managers, and emergency responders over the near-term (e.g., 2040–2060).

Conversely, the drying trend is predicted to reduce flammability at lower elevation as fuel production becomes more limited under arid conditions (Bradstock, 2010), which may reduce risk around residential areas. Future population growth will likely increase ignition density (Trauernicht et al., 2015b) but because most ignitions occur along roads and communities, it is also possible that the shift in future flammability upland and away from inhabited areas reduces the potential for fire in the landscape. Yet despite the decreasing flammability in lowland areas, the results indicate that fire probability will increase by as much as 375% by the late 21st Century under the RCP 8.5 scenario (Fig. 4e–h) and that the largest increases will occur at higher elevations (i.e. 1000–2000 m) than current, peak landscape flammability (Fig. 6g, h). It is important to note, however, that the range of annual climate variability produces flammability predictions that are comparable future conditions in terms of median and maximum increases in flammability (Fig. 5). This implies that the worst fire years in recent history at least provide a baseline from which to understand and anticipate future risk, although the effects of rainfall anomalies under future conditions was not assessed.

4.4. Applications

This modeling framework was explicitly developed in a decision-making context in which landowners and land managers wanted to understand how projected changes in rainfall and proposed re-forestation would alter fire risk and other landscape values at the watershed scale (Bremer et al., 2018; Wada et al., 2017). Importantly, by capitalizing on existing data and avoiding the assumptions of more complex models of fire spread, this approach may be applied in other regions of the world similarly underserved by fire science. In addition, relatively simple model assumptions can facilitate the communication of fire risk to relevant decision-makers (Schmolke et al., 2010). In Hawaii, for instance, predictive fire models developed for the US mainland are notorious for poor performance, while investment in model calibration has not kept pace with increasing impacts and risk of wildland fire (Beavers et al., 1999; Benoit et al., 2009; Pierce et al., 2014). As a result, agencies are often skeptical of relying on models and/or investing in the technical capacity to implement fire modeling (Gollin and Trauernicht, 2018). The use of the habitat modeling approach and a logistic regression framework to model the likelihood of fire occurrence is not new (Hoyos et al., 2017; Parisien and Moritz, 2009; Paritsis et al., 2013; Preisler et al., 2004), but its application in the context of landscape flammability in Hawaii holds promise in addressing these concerns.

5. Conclusion

By attributing fire occurrence across the landscape to available metrics of vegetation, mean and annual climatic conditions, and ignitions, the approach presented here provides a way to quantify both the variation in and the degree to which different factors contribute to landscape flammability. As with any modeling approach, there is always room for improvement. The application of remote sensing for fire mapping in Hawaii is increasing the temporal and spatial precision of fire perimeter data (Hawbaker et al., 2017). These improvements and the release of daily historical rainfall data for Hawaii (Longman et al., 2018) will enable future analyses to include climate data at finer temporal resolutions that will likely increase model performance. In addition, and partially in response to the limitations of this analysis, satellite imagery is also being used to develop annual maps of land cover to account for changes in land cover/land use that may alter fire probability and provide continuous (e.g., percent forest cover) values vs. discrete categories of land cover types which should improve model predictions (Lucas, 2017). Despite the limitations of the current model to account for more rapid fluctuations in fire risk caused by weather and ignition variability, the framework provides a robust approach to assessing the influence of annual variability relative to mean climatic conditions as well as the spatial patterns in current and future fire risk. These results not only provide a novel perspective on fire regimes in Hawaii, but frame fire risk factors in a temporal and spatial context that has practical value for prioritizing and planning mitigation actions.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.08.347.

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