CSIRO PUBLISHING

International Journal of Wildland Fire **2014**, *23*, 1108–1118
http://dx.doi.org/10.1071/WF13115

Modelling and mapping dynamic variability in large fire probability in the lower Sonoran Desert of south-western Arizona

Miranda E. Gray[A,C], *Brett G. Dickson*[A,B] *and Luke J. Zachmann*[A,B]

[A]Laboratory of Landscape Ecology and Conservation Biology, Landscape Conservation Initiative, Box 5694, Northern Arizona University, Flagstaff, AZ 86011, USA.
[B]Conservation Science Partners, Inc., 11050 Pioneer Trail, Suite 202, Truckee, CA 96161, USA.
[C]Corresponding author. Email: miranda@csp-inc.org

Abstract. In the lower Sonoran Desert of south-western Arizona, climate change and non-native plant invasions have the potential to increase the frequency and size of uncommon wildfires. An understanding of where and why ignitions are more likely to become large fires will help mitigate the negative consequences of fire to native ecosystems. We use a generalised linear mixed model and fire occurrence data from 1989 to 2010 to estimate the relative contributions of fuel and other landscape variables to large fire probability, given an ignition. For the 22-year period we examined, a high value for the maximum annual Normalised Difference Vegetation Index was among the strongest predictors of large fire probability, as were low values of road density and elevation. Large fire probability varied markedly between years of moderate and high fine fuel accumulation. Our estimates can be applied to future periods with highly heterogeneous precipitation. Our map-based results can be used by managers to monitor variability in large fire probability, and to implement adaptive fire mitigation at a landscape scale. The approaches we present have global applications to other desert regions that face similar threats from changing climate, altered fuels and potential punctuated changes in fire regimes.

Additional keywords: desert fire management, generalised linear mixed model, invasive plant–fire cycle, multi-model inference, NDVI.

Received 17 July 2013, accepted 18 June 2014, published online 14 November 2014

Introduction

Invasions by non-native plants as well as global climate and land cover changes are introducing novel and deleterious fire regime characteristics to sensitive desert ecosystems worldwide (D'Antonio 2000). In low-elevation deserts of western North America, where perennial vegetation productivity is typically low, long fire-return intervals and small patchy fires likely characterise native fire regimes (Brooks and Minnich 2006). Disruption of these fire regimes, in the form of larger and more frequent fires, can diminish the long-term recovery potential of native plant communities with limited resilience (Brooks and Chambers 2011). These disruptions can lead to alternative stable states dominated by non-native plants (D'Antonio *et al.* 2009), which has occurred to a limited extent in middle and low elevations of the Sonoran Desert (Esque and Schwalbe 2002; Brooks and Minnich 2006). Large fires can also result in significant reductions in habitat use by vulnerable wildlife that rely on mature desert communities (e.g. Esque *et al.* 2013).

In systems where fine fuels control the spread of fire, up to 2 years of above-normal antecedent precipitation can drastically change fuel loads and the likelihood of large fire (Littell *et al.* 2009; Krawchuk and Moritz 2011). These climate-driven increases in fuel can be accompanied by very large increases in the inter-annual and spatial variability of large fire occurrence (Brooks and Matchett 2006; Littell *et al.* 2009). Ignition source, weather patterns and moisture deficits in a given fire season are among the key factors that may influence this variability (Littell *et al.* 2009; Abatzoglou and Kolden 2013). By identifying where large fires are more likely to occur in any given year due to fuel loads and other landscape variables, managers would be better equipped to control for this variability and adapt their actions. The LANDFIRE project (http://www.landfire.gov, accessed August 2014) is one source of national-scale data that has been used to inform assessments of fire threat, including large fire probability (e.g. Finney *et al.* 2011). LANDFIRE fuels data were most recently updated to reflect vegetation change and disturbance from 1999 to 2010, but the temporal resolution is still too coarse to accommodate the highly ephemeral nature of deserts, where fuel loads can change dramatically on an annual time scale.

In desert regions, statistically robust estimates of annual large fire occurrence need to account for the high levels of heterogeneity in precipitation and fuel growth that typically precede a fire event. Mixed models, which include both random and fixed effects (i.e. variables), provide a multi-level modelling structure to account for both of these variables while minimising confounding influences and allowing for more robust estimates of fixed effects (Faraway 2006). The Normalised Difference Vegetation Index (NDVI) is a spectral index derived from remote sensing that indicates plant biomass, vigour and greenness, and has been used in parts of the Sonoran and Mojave Deserts to estimate dynamic fuel availability at regional extents (Casady *et al.* 2013; Van Linn *et al.* 2013). The availability of high spatial and temporal resolution NDVI makes it a useful variable for estimating the direct (and fixed, but unknown) effect of highly dynamic fuel growth on large fire occurrence. Precipitation can be invoked as a random effect in a model of large fire occurrence to control for broad-scale patterns of inter-annual variation (and any associated correlation structure) in fire observations. By including it as a random effect, precipitation variability is also identified explicitly and the scope of inference can be extended to future periods (Gillies *et al.* 2006).

The lower Sonoran Desert of south-western Arizona is generally too dry to support native vegetation that is sufficient to carry large fires (Humphrey 1974). Prior to the grazing and fire suppression era, fires in this system were infrequent and small (Brooks and Minnich 2006). However, >70 000 ha have burned since 2000, with most (>75%) of this area burning in 2005. Although it is difficult to know if this pattern represents more frequent burning than has occurred in the past, conditions favourable to large fire occurrence are likely to increase in the Sonoran Desert (Abatzoglou and Kolden 2011). Accordingly, land managers would benefit from information to help monitor large fire occurrence and adapt to dynamic changes in the environment, including fuels. Managers in the region are particularly concerned about the establishment of non-native, fire-adapted grasses and forbs that introduce a novel fuel source to the environment. These include red brome (*Bromus rubens*), Mediterranean grass (*Schismus arabicus* or *S. barbatus*) and Sahara mustard (*Brassica tournefortii*). Like many of the native annual plants in the Sonoran Desert, these non-native annual plants typically germinate in early winter and respond vigorously to environmental fluctuations driven by rainfall (Venable and Pake 1999). Poorly planned land use and restoration efforts could further benefit these and other invasive plant species if they do not account for the anticipated effects of climate variability and change (Bradley *et al.* 2010).

In this context, the objectives of our research were to model and map the probability that an ignition in the lower Sonoran Desert of south-western Arizona will result in a large fire (henceforth referred to as large fire probability), and to apply an improved understanding of the dynamic variability in large fire probability to recommendations for fire management. Specifically, we sought to (1) capture variability in available fuels by deriving estimates of maximum annual NDVI for 1988–2010 from satellite imagery; (2) use a generalised linear mixed model to estimate large fire probability, which treats antecedent winter precipitation as a random effect and fuel availability and other landscape variables as fixed effects; (3) extend this model to produce high spatial resolution (i.e. 30 m) and up-to-date maps of large fire probability across multiple jurisdictions; and (4) use these results to explore patterns of large fire probability that can inform future management activities concerned with mitigating the individual or synergistic effects of fire and non-native plant invasion in Sonoran Desert lowlands.

Materials and methods

Study area

The 45 100-km^2 study area is located in south-western Arizona, USA, and encompasses multiple jurisdictions that include vast areas of Bureau of Land Management land, the USA Army Yuma Proving Ground (YPG; 3360 km^2), the Barry M. Goldwater Air Force Range (BMGR; 7070 km^2), as well as the Kofa (KNWR; 2690 km^2) and Cabeza Prieta National Wildlife Refuges (CPNWR; 3468 km^2) (Fig. 1). Mean elevation is 372 m (s.d. = 182 m) and ranges from 26 m in the south-western lowlands to 1480 m on the KNWR. Lower elevations (<600 m) primarily encompass the Lower Colorado River subdivision of the Sonoran Desert (Brown 1994). This subdivision is among the most arid of the North American deserts and is characterised by sparsely vegetated desert shrublands dominated by creosote bush (*Larrea tridentata*) and white bursage (*Ambrosia dumosa*) (Brown 1994). Areas of higher topographic relief fall within the Arizona Upland subdivision of the Sonoran Desert and generally support more diverse perennial plant cover (Brown 1994; Phillips and Comus 2000). Mean minimum (December) and maximum (July) temperatures range between 5.9°C (YPG) and 39.8°C (KNWR). Of the long-term (1952–2012) average annual precipitation at the YPG (95 mm) and KNWR (162 mm), 58 and 92 mm fell in the winter (December–February). The winter of 2004–05 was particularly wet for this region, recording more than 300% of the average winter precipitation across the study extent (Western Regional Climate Center, http://wrcc.dri.edu/, accessed December 2012). An increase in cool season precipitation variability over the past half century, coupled with disturbance from land use (e.g. agricultural) activities, have facilitated increased invasion by non-native plants (Abatzoglou and Kolden 2011). Since 2000, increased temperature and reduced humidity in the spring and summer months have also increased the frequency of days with extreme fire danger (Abatzoglou and Kolden 2011).

Fire occurrence data

We compiled fire occurrence data for 1989–91 from the dataset described in Finney *et al.* (2011) and for 1992–2010 from the Fire Program Analysis Fire Occurrence Database (FPA FOD; Short 2013). These data included natural- and human-caused ignition points on both federal and non-federal lands, as well as the latitude and longitude of the point of origin, date of ignition and total area burned. We characterised all fires that burned during the study period as either 'large' (i.e. ≥20 ha) or 'small' (i.e. <20 ha) fires. Twenty hectares represents a low-end estimate of large fire size in desert fuels and is a threshold that characteristically separates years when the annual fuel load is sufficient for fire spread (W. Reaves, pers. comm.).

Landscape variables

We used a circular moving window operation and focal statistics in a geographic information system (GIS; ArcGIS v10.1, Redlands, CA, USA) to summarise each of the following landscape variables within a 20-ha neighbourhood around each ignition point. Although this approach was designed to encompass the landscape factors that influence fire size within our large fire threshold, it may not adequately account for the

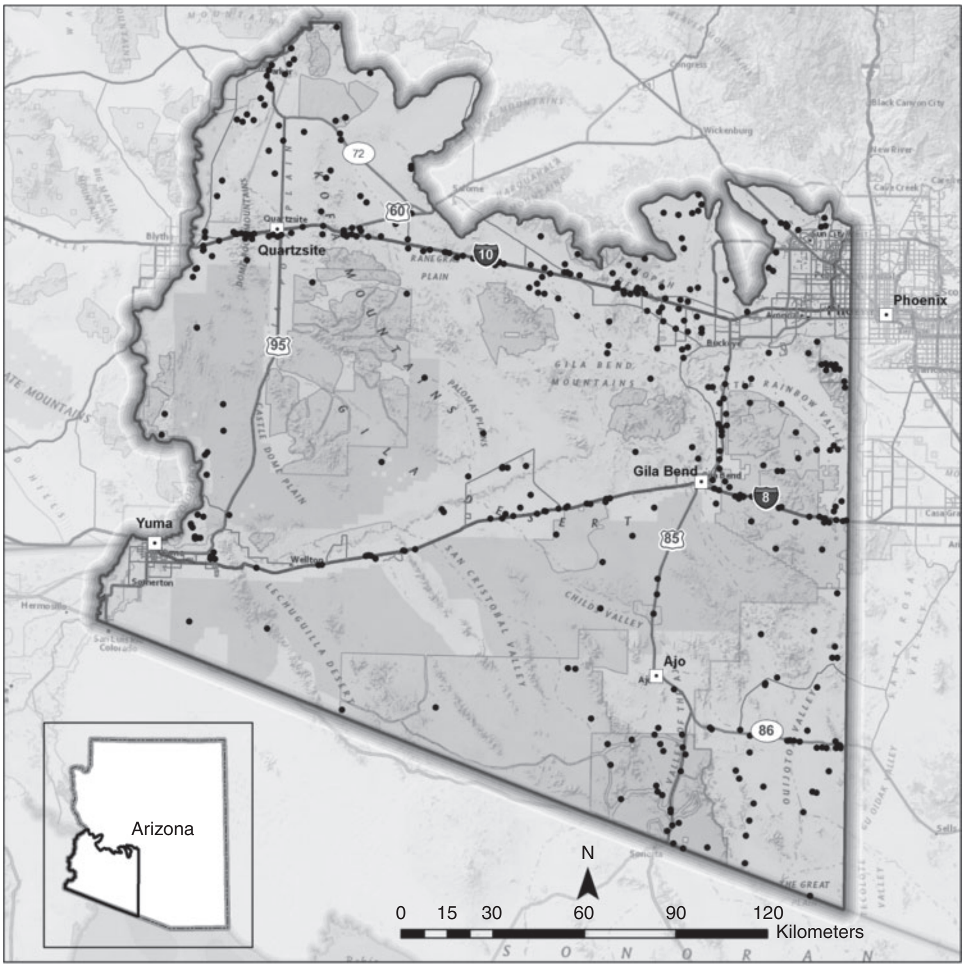

Fig. 1. The 45 100-km^2 study area used to model large fire probability in the lower Sonoran Desert of south-western Arizona, 1989–2010. Black dots represent fire ignition points recorded during the analysis period.

full array of factors that influence fire growth beyond 20 ha. All landscape variables were derived as or converted to raster grids with a 30-m pixel resolution. For all landscape variables except the maximum NDVI, we standardised and rescaled values to a mean of zero and unit variance at the full extent of our study area. We used the 'raster' package (Hijmans and Van Etten 2012) in R 2.15.1 (R Development Core Team 2011) to extract landscape variables from each ignition point before statistical analysis.

We accounted for the direct effect of fuel loads on large fire probability using a time series of the maximum annual NDVI. We expected yearly maximum NDVI to be useful for detecting dramatic fluctuations of annual fine fuel accumulation (Casady *et al.* 2013). To estimate yearly maximum NDVI values for 1988–2010 – the period coinciding with our fire occurrence dataset – we obtained Landsat Thematic Mapper (TM) scenes covering our study area (n = 1114, temporal resolution = 16 days) from the US Geological Survey (USGS) Global Visualisation Viewer (http://glovis.usgs.gov, accessed November 2012) and atmospherically corrected all images using ENVI 4.7 software (Exelis Visual Information Solutions, Boulder, CO, USA). Our model included variables of the year-of-fire maximum NDVI value as well as the maximum NDVI value of the year before the fire. The lagged year variable was included to account for senesced biomass that remained standing as fuel for a subsequent fire season, designated as April–June for this region (Crimmins and Comrie 2004).

Within the GIS, we derived an NDVI-based variable to represent the horizontal spatial structure of perennial vegetation. Similarly, previous research in the Mediterranean region of Spain successfully used Landsat TM to characterise the horizontal heterogeneity of vegetation by taking the standard deviation of Landsat bands in a local window (Vega-García and Chuvieco 2006). Therefore, we approached our work in the context of far-reaching, uniform shrublands and sparsely vegetated areas in the Sonoran Desert, where large interspaces have been observed to amass continuous fine fuels after heavy precipitation. We hypothesised that these homogenous communities favoured the spread of fire, following wet conditions that would propagate fine fuels. Our variable for perennial vegetation heterogeneity was the standard deviation of maximum NDVI in 1989 – a dry year when NDVI was most likely dominated by perennial growth.

Our modelling approach also accounted for multiple terrain variables that directly influence fire spread and indirectly influence vegetation growth and flammability (Syphard *et al.* 2008). Using a digital elevation model obtained from the USGS (http://ned.usgs.gov/, accessed March 2011), we derived estimates of elevation, aspect (in degrees), and terrain roughness (standard deviation of slope; Preisler *et al.* 2011) within the GIS. We used the cosine transformation of aspect to provide an index that ranged between −1 (180°, south-facing slopes) and 1 (0 or 360°, north-facing slopes).

Our study area included large expanses of federal and military lands with limited or no public road access, which we expected to have a positive influence on large fire probability (Hawbaker *et al.* 2013). Therefore, we used the GIS and 2011 US Census Bureau TIGER line data (http://census.gov/geo/www/tiger, accessed November 2011) to estimate a simple road density (km km^{-2}) variable that could serve as a proxy for human accessibility and help to differentiate where fires were more or less likely to become large.

Statistical and spatial modelling

We used mixed-effects logistic regression to estimate large fire probability, conditioned on the seven explanatory variables (i.e. fixed effects) described above. The binary response in this model was an ignition event that resulted in either a large ('1') or small ('0') fire. Therefore, our derived estimates were conditional probabilities of large fire given an ignition (Preisler *et al.* 2004). A random sample of small fires ($n = 371$) was eliminated from our dataset so as to arrive at a more parsimonious 4 : 1 ratio of small to large fires (Brillinger *et al.* 2003; Syphard *et al.* 2008). This sampling scheme was expected to produce smaller standard errors without biasing the estimates of our regression coefficients (Allison 2012).

We included the winter precipitation anomaly immediately preceding a fire event and one lag season precipitation anomaly as crossed random effects (Bolker *et al.* 2009). Precipitation anomalies, based on 1981–2010 normals, were derived from 800-m gridded data as the percentage of normal precipitation from October through March (Western Regional Climate Center, http://wrcc.dri.edu/monitor/WWDT/archive.php, accessed November 2011). For parsimony, and to account for the variance associated with winter precipitation totals, we categorised each random effect into five quantiles. We used the raster package in R to extract the year-of-fire and lag year winter precipitation anomaly from each ignition point before statistical analysis.

To account for any spatial autocorrelation present in the fire occurrence data, we applied an unbiased covariance estimator for cluster-correlated data (Williams 2000; Bigler *et al.* 2005). Specifically, this 'sandwich' estimator allowed for arbitrary dependence structure among clustered response data and relaxed assumptions of constant variance in the residuals. We used this estimator to compute the variance–covariance matrix of the fixed effect parameters.

We used an information–theoretic approach and multi-model inference to estimate and evaluate the importance of explanatory variables (Burnham and Anderson 2002) within a 'full' model that included all seven fixed effects and two random effects. We used maximum likelihood to estimate model-averaged regression coefficients ($\bar{\bar{\beta}}$) for our fixed effects and Akaike's Information Criterion (AIC) to evaluate model selection uncertainty and reduce model selection bias (Burnham & Anderson 2002). We computed AIC weights (w) to evaluate the weight of evidence in favour of a fixed effect variable, based on all combinations of variables (Burnham and Anderson 2002; Doherty *et al.* 2012). Specifically, we summed the AIC weights across all models in which a given variable (j) occurred and considered a cumulative AIC weight ($w_+(j)$) $\geq$0.50 to be strong evidence for a response to that variable (Barbieri and Berger 2004). We used the difference in AIC (ΔAIC) values to evaluate the performance of the full model against a null model with only random effects, and considered a ΔAIC value >4.0 to be a good approximation of the data (Burnham and Anderson 2002). We also used ΔAIC values to evaluate the performance of the full model using all fire occurrences to the reduced dataset model (i.e. with a 4 : 1 ratio). We used the Hosmer–Lemeshow statistic to evaluate goodness of fit ($\alpha = 0.05$; Hosmer and Lemeshow 2000). To evaluate model classification accuracy, we computed the area under the receiver operating characteristic (ROC) curve (Hosmer and Lemeshow 2000). This ROC value provided a likelihood-based measure of discrimination between predicted small and large fire occurrence. We considered ROC values >0.70 as indicative of good discrimination (Hosmer and Lemeshow 2000). We conducted all of the above analyses using R 2.15.1 (R Development Core Team 2011) and SAS 9.2 software (SAS Institute Inc., Cary, NC, USA).

We used the model-averaged regression coefficients and GIS to implement the full model and produce probabilistic, spatially explicit maps for two analysis years (1996 and 2005) at a 30-m pixel resolution. We chose these years to illustrate dynamic large fire probability in a moderate fine fuel scenario (1996) and high fine fuel scenario (2005), and we refer to these as moderate and high large fire probability scenarios. For 1996, we reasoned that fuel loads were affected primarily by the wet winter of 1994 and therefore only moderately abundant. Fine fuels were uncharacteristically abundant across the study area in 2005 (see below).

Results

Fire occurrence

The compiled fire occurrence dataset included 316 small and 79 large fires that burned within the study area between 1989 and 2010. Over these 22 years, a total of 57 000 ha burned in large fires. The year 2005 resulted in the greatest number of large fires ($n = 36$) and total area burned (51 700 ha). The median size of a large fire in 2005 was 95 ha, whereas the 22-year median size of a large fire was 60 ha. A pilot analysis of NDVI values preceding a subset of large fires in 2005 indicated a strong relationship between annual NDVI values and large fire occurrence (Fig. 2).

Statistical and spatial modelling

Our full model of large fire probability was 71 AIC units lower (i.e. better) than a null model containing only the random effects. The full model that was implemented with all fire

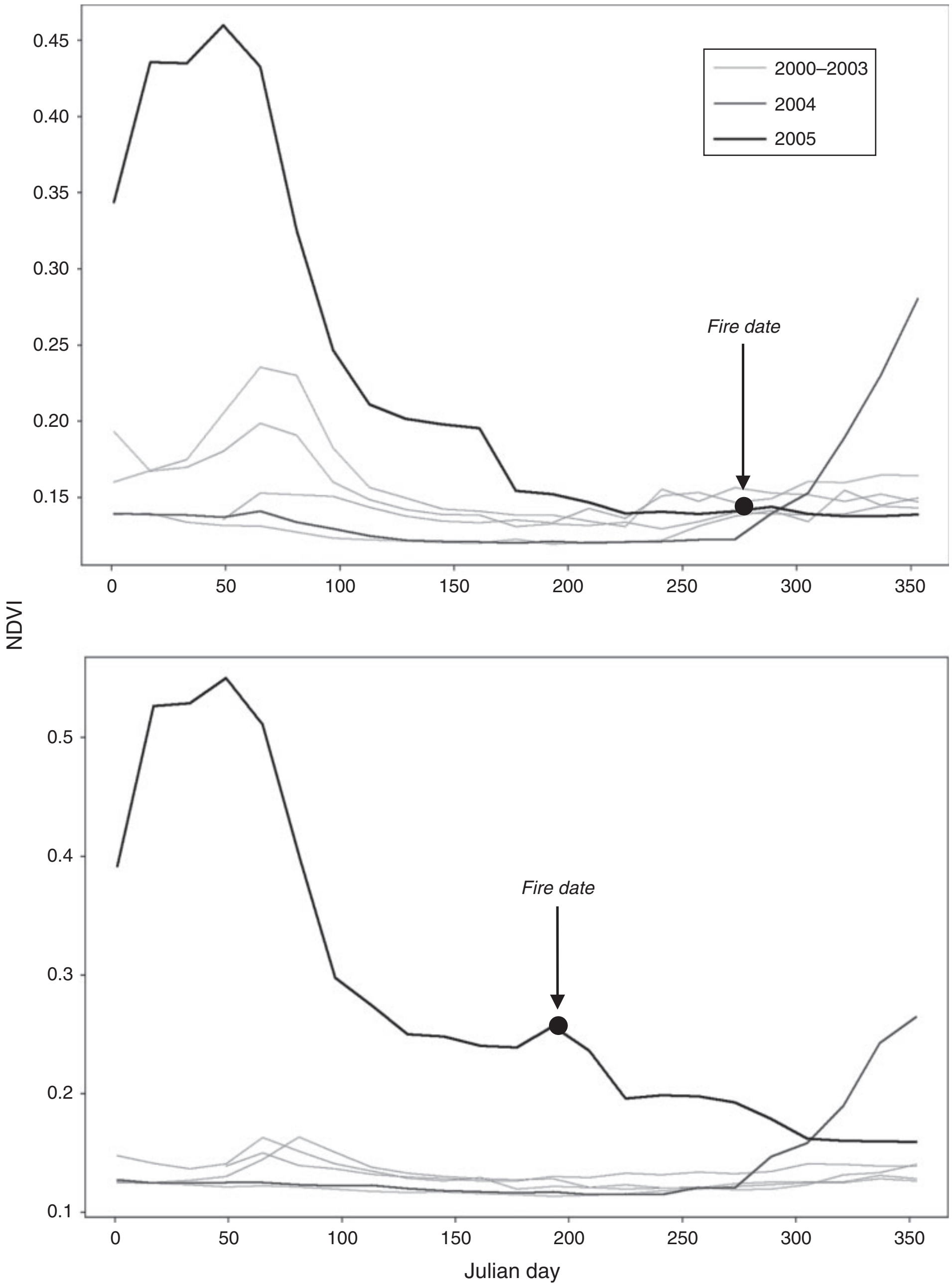

Fig. 2. Trends in the Normalized Difference Vegetation Index (NDVI) from 2000–2005 within the perimeter of two large fire events. Relative to background years (i.e., 2000–2003), there was a dramatic increase in NDVI in the winter of 2004 and leading into 2005. The King Valley fire (top) burned in September–October 2005, and the Goldwater fire (bottom) burned in June 2005.

occurrences was 58 AIC units lower than the null model. This 13-unit difference suggests that less information (i.e. more 'noise') was present in the larger dataset. Thus, we proceeded with model evaluation and inferences based on the reduced dataset that included 316 small and 79 large fires. The Hosmer–Lemeshow test did not indicate a significant lack of fit ($P = 0.25$). The ROC value for this model was 0.85, indicating excellent discrimination. Among the explanatory variables we evaluated, areas with high maximum annual NDVI ($w_+(j) = 1.00$), low elevation (1.00) and low road density (1.00) were the most strongly associated with higher large fire probability (Table 1). Low vegetation heterogeneity was a strong predictor (0.90), as were south-facing aspects (0.80). The lagged variable of maximum NDVI was not as influential as the year-of-fire maximum NDVI, but was still a strong predictor (0.70). Topographic roughness also was a strong predictor of large fire probability (0.58), but less of a driver than the other variables we considered.

Table 1. Explanatory variables (fixed effects) used to estimate large fire probability in the lower Sonoran Desert of south-western Arizona, 1989–2010

Cumulative Akaike's Information Criterion weights (w_+ (j)), model-averaged regression coefficients ($\tilde{\tilde{\beta}}$) and unconditional standard errors (s.e.) were estimated with logistic regression using all possible subsets ($n = 128$) of the full model. The binary response in the model was 'small' or 'large' fire. NDVI, Normalised Difference Vegetation Index

Variable	w_+ (j)	$\tilde{\tilde{\beta}}$	s.e.
Maximum annual NDVI	1.000	0.047	0.008
Road density	1.000	−0.974	0.238
Elevation	1.000	−0.958	0.223
Vegetation heterogeneity	0.903	−0.742	0.425
Aspect (north-ness)	0.801	−0.262	0.189
Lag-1 maximum NDVI	0.704	0.013	0.011
Topographic roughness	0.579	0.191	0.220
Intercept	–	−4.251	0.621

Table 2. Best linear unbiased predictors of random effects used to estimate large fire probability in the lower Sonoran Desert of south-western Arizona, 1989–2010.

Levels of the random effects represent the precipitation anomaly in the winter season immediately before fire season (i) or in the lag year winter season (j). PON, percentage of normal precipitation based on 1981–2010 normals. γ, best linear unbiased predictor

Level	PON	γ
(i)		
1	4.4–43.3	−4.041
2	43.3–91.7	−4.635
3	91.7–163.0	−4.413
4	163.0–238.0	−3.656
5	238.0–324.0	−4.452
(j)		
1	7.3–54.3	−4.858
2	54.3–81.2	−4.119
3	81.2–141.0	−3.672
4	141.0–191.0	−4.231
5	191.0–314.0	−4.311

The random effects ranged from <10 to >300% of normal winter precipitation (Table 2). The best linear unbiased predictors for the random effects (Faraway 2006) revealed that precipitation anomaly in the two antecedent winters had different predicted effects on large fire probability, but without any discernible pattern (Table 2).

Maps of the moderate (1996; Fig. 3) and high probability (2005; Fig. 4) scenarios showed very different patterns of large fire probability across the study area. In 1996 there were only a few isolated patches of very high large fire probability (e.g. >60%), whereas in 2005 very high probability was much more widespread and spatially contiguous. Considering the entire study area, the mean probability of large fire was 0.13 (s.d. = 0.08) and 0.37 (0.21) in 1996 and 2005.

Discussion

In the face of ongoing climate and land cover changes, our results provide a timely assessment of large fire occurrence. When exposed to fire sizes and frequencies outside of their historical range of variability, desert ecosystems with a low resilience to fire are especially susceptible to vegetation type conversion dominated by invasive plant species (D'Antonio *et al.* 2009). In hot desert shrublands, resilience to fire and resistance to type conversion tends to decrease from high to low elevations, where fires have historically been the least frequent (Brooks and Chambers 2011). This trend predisposes the lowest elevations of the Sonoran Desert to rapid environmental change if fire frequency increases. The relative importance and influence of landscape variables lend insight into the drivers of large fire and are robust to variability in winter precipitation that might be recorded over a given 22-year period.

Highly heterogeneous precipitation and fuel growth in the lower Sonoran Desert should be accounted for in a model of large fire probability. Our modelling approach was focussed on estimating the fixed effect of dynamic fuels, largely because reliable data to represent fuels is available at high spatial and temporal resolutions. NDVI data were derived directly at a 30-m resolution, and provided a continuous measure of plant vigour and biomass that was congruent with the high spatial resolution of other important landscape variables. In contrast, precipitation data are often only available at a coarse spatial resolution, and in our case were derived from 4-km resolution, interpolated data. We chose to represent precipitation as a categorical, random effect of precipitation anomaly in order to capture low-level variation in large fire probability over time. This mixed model approach allowed us to integrate the important effects of both antecedent winter precipitation and fuel growth into models and maps of large fire probability.

Perhaps not surprisingly, areas of high probability shifted over the analysis period and were strongly influenced by values for annual maximum NDVI. Significant increases in fine fuels that contribute to changes in large fire probability can be comprised mostly of non-native biomass or mostly of native biomass (Esque and Schwalbe 2002; Brooks and Matchett 2006). Infrequent years of high rainfall can permit native annuals to contribute sufficient biomass to carry fire through the interspaces among larger perennial plants (Brooks and Minnich 2006). For example, the native annual desert Indian wheat (*Plantago ovata*) fuelled a large fire event in our study area in 2005 and fire effects were consistent with those observed from fires fuelled by non-natives (Esque *et al.* 2013). Nevertheless, recent invasions by non-native annual plants provide a significant new fuel source that may act to amplify fire–climate relationships in the Sonoran Desert region (Esque and Schwalbe 2002). Mediterranean grass species, given their tolerance for extreme drought, are capable of proliferating in this harsh and changing environment and have the potential to establish more persistent and contiguous fuel beds than native annuals (Brooks and Minnich 2006). Similarly, Sahara mustard is likely to augment the fine fuel bed when conditions are appropriate (Brooks and Pyke 2001). This highly invasive forb can grow >1 m high and >1 m wide, and is a prolific seed producer (Brooks and Minnich 2006). The potential for both native and

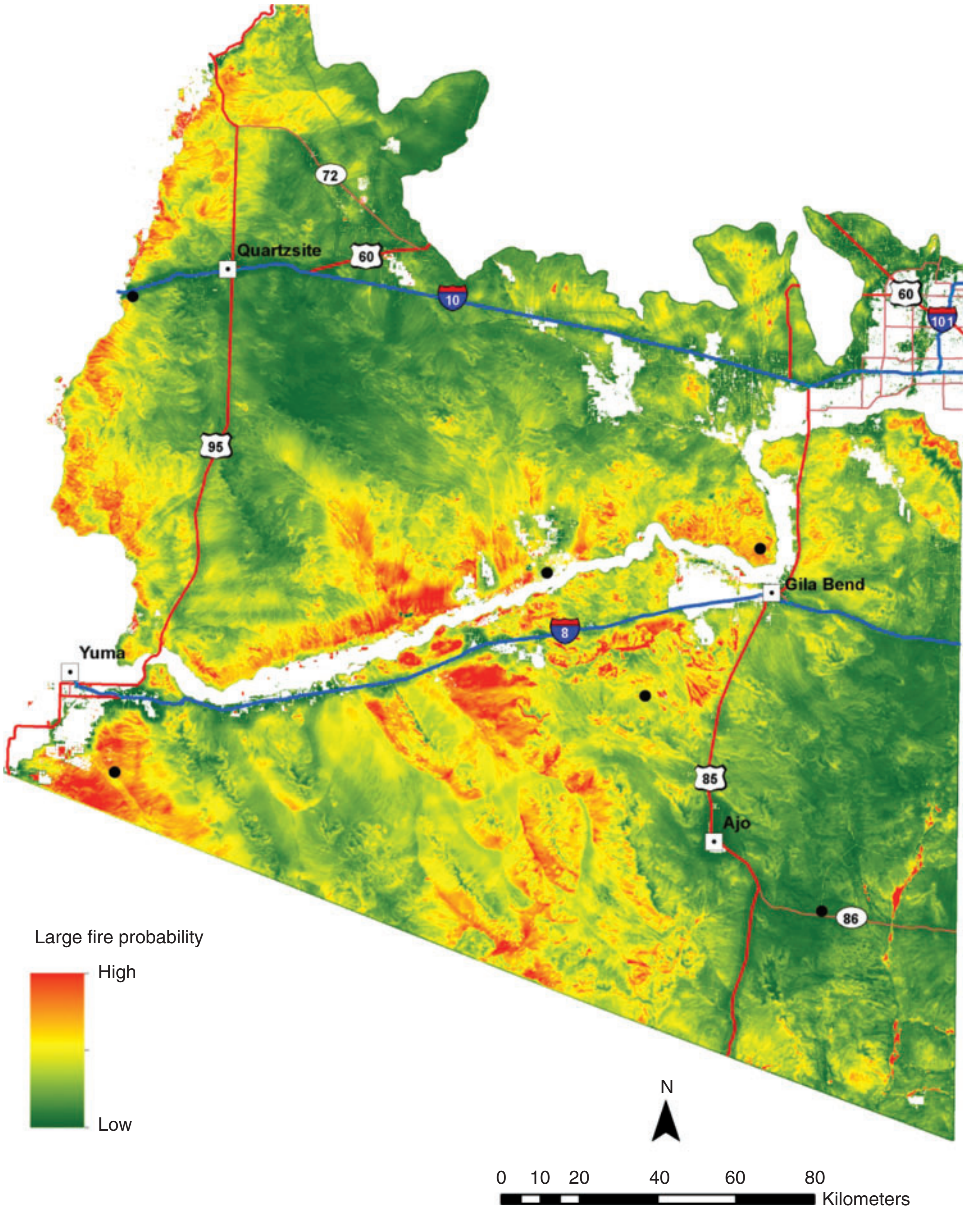

Fig. 3. Map-based prediction of large fire probability in the lower Sonoran Desert of south-western Arizona, based on 1996 conditions (i.e. moderate large fire probability). The ignition points of large (≥20 ha) fires that burned in 1996 are represented by black dots.

non-native plants to alter fire regimes highlights the importance of monitoring the total accumulation of grasses and forbs. Since the influence of maximum NDVI on large fire probability does not distinguish between native and non-native plants, it is an important proxy for total fuel accumulation in the lower Sonoran Desert.

High values for maximum NDVI in the year before large fire occurrence demonstrated that annual plants might remain available to fuel large fires in the subsequent fire season. This pattern may become even more important with changing fuel conditions and composition. For example, Mediterranean grass species tend to decompose more slowly than native grasses and persist longer into subsequent years (Brooks and Minnich 2006). The predictive capacity of both year-of-fire and lag year NDVI variables provides a powerful forecasting tool, or 'early warning system', for land managers concerned with fire.

Our results suggested that lower elevations had a higher probability of large fire, given an ignition in the period we examined. These areas generally comprise the Lower Colorado River subdivision and are expected to exhibit lower fire resilience, such that native vegetation could be more vulnerable to the effects of repeated fire. Four of the largest fires that collectively burned >50 000 ha in 2005 all burned between elevations of 160 and 600 m. If similar fuel conditions

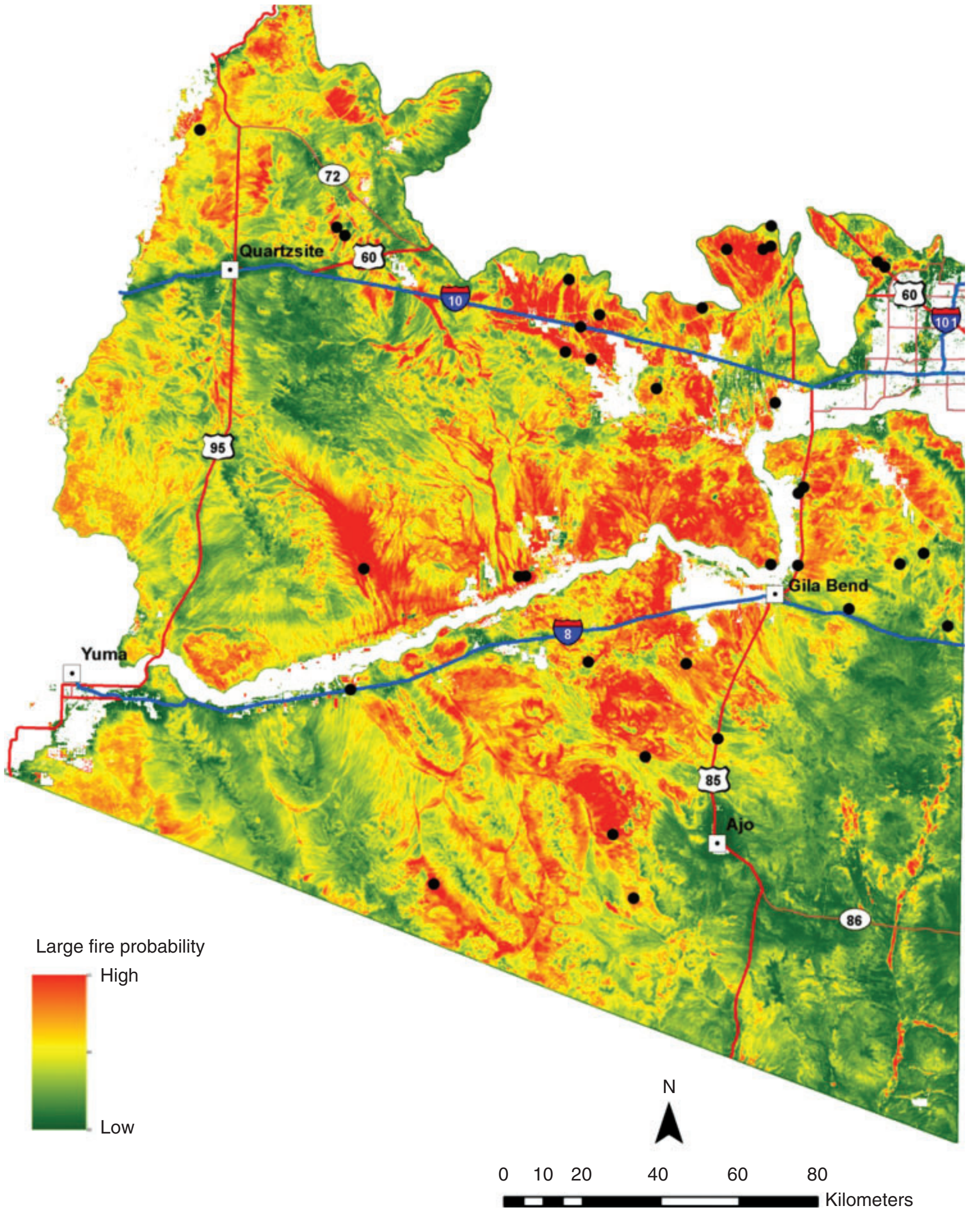

Fig. 4. Map-based prediction of large fire probability in the lower Sonoran Desert of south-western Arizona, based on 2005 conditions (i.e. high large fire probability). The ignition points of large (≥20 ha) fires that burned in 2005 are represented by black dots.

persist, future repeated fire events in low-elevation areas have great potential to initiate an invasive plant–fire cycle and homogenise vegetation composition and structure over large areas (D'Antonio and Vitousek 1992).

Although proximity to roads is likely a strong driver of fire ignition (Fig. 1), we found that the probability of an ignition becoming a large fire is highest in areas of low road density. We attribute this primarily to difficult access for fire suppression efforts (Dickson *et al.* 2006). Fire spread rates typically are highest in grass and shrubland fuels and fire can quickly grow larger in more remote regions (Scott and Burgan 2005). Indeed, our study region comprises vast roadless and designated wilderness areas, as well as military installations where limited accessibility is likely to hinder fire suppression. For example, in 2005, the 13 000-ha King Valley fire started in an isolated area of the YPG and quickly spread to the adjacent KNWR wilderness. The 11 000 ha Growler Peak fire of 2005 spread mostly in the less frequented areas of the BMGR.

Our results showed that some of the most common vegetation communities in the region might be especially prone to large fires when fuel conditions are favourable. For example, perennial vegetation homogeneity contributed to higher probability of large fire during the analysis period, as indicated by contiguous areas of similar NDVI signal. Open desert shrub communities of creosote bush and white bursage extend for thousands of hectares in the low bajadas and plains of our study area (Phillips and Comus 2000). A high degree of homogeneity related to dominant perennial vegetation would likely represent the conditions where uniform structure and interspaces are present, or areas that are perennially sparsely vegetated. With sufficient precipitation, these interspaces and barren surfaces can become contiguous fuel beds that facilitate the spread of fire.

We found that south-facing aspects, which face the direction of prevailing winds out of the south and south-west, facilitated large fires. Perhaps this is not surprising since south-facing aspects tend to be more arid environments for vegetation. Indeed, the maximum effect of weather, topography and fuel on fire spread occurs when wind direction is directly aligned with aspect (Whelan 1995). Thus, the effects of aspect on spreading fire fronts and on fuel characteristics and flammability likely combined to influence large fire probability during the period we examined.

The combined influence of topographic roughness and elevation indicated that fires are more likely to become large in low elevations with somewhat rough terrain. This pattern suggests greater probability of large fires in low-lying xeroriparian networks, which are micro-topographic features widespread throughout our study area. These ephemeral networks can support a high density of plant species after seasonal pulses of rainfall and flood flows, which are capable of sustaining the spread of fire (Stromberg *et al.* 2009). Changes in xeroriparian plant communities can affect an array of ecosystem functions and uncharacteristic fire should be considered a potential stressor (Stromberg *et al.* 2009).

Conclusions and management implications

Our modelling approach and associated map products can be used to monitor ignitions and mitigate the occurrence or negative consequence of large fire in the lower Sonoran Desert. Maps of large fire probability will be useful for management decisions such as fuels reductions, prevention programs to curb human-caused ignitions and suppression planning in advance of fire occurrence that could result in more rapid response. Our scenario-based maps will allow managers to base these decisions on empirical average and 'worst-case' conditions reflected by the 22-year time period we examined. For instance, management actions based on the high-probability scenario could make the landscape more resilient to extreme events such as those that occurred in 2005. These activities, including implementation of adaptive prevention and suppression plans, will be especially important when and where fire season weather is extreme and likely to exacerbate the probability of an ignition becoming a large fire over time.

Scenario-based maps of large fire probability also can be used to establish spatially referenced plots for the targeted and long-term observation of fuel conditions. For instance, managers can use these maps together with modelled habitat of non-native plants to determine where large fires might initiate or exacerbate positive feedbacks between invasive plants and fire (Brooks and Chambers 2011). In this case, managers might be interested in monitoring areas under both moderate- and high-probability scenarios, as these areas might signal where the invasive grass–fire cycle is more likely to establish even under average conditions.

Lastly, our model-averaging approach provides interpretable, relative measures of importance for the explanatory variables that drive large fire probability. Given the high relative importance of maximum annual NDVI, managers should be aware of NDVI patterns that precede the onset of the fire season, which can be easily monitored on an annual basis. The availability of high spatial and high temporal resolution satellite imagery (e.g. Landsat TM or Moderate Resolution Imaging Spectroradiometer (MODIS) data) permits the practical integration of time series NDVI into fire forecasting. For example, time series of NDVI data can be used to monitor dramatic fluctuations in winter annual production that would indicate increases in the probability of ignitions becoming large fires (Casady *et al.* 2013). Relative to maximum annual NDVI, low-elevation areas with low road densities also are strong contributors to large fire probability and should be considered important in fire planning decisions. In general, managers can use the relative importance of variables to prioritise decisions that mitigate negative fire effects across the lower Sonoran Desert region.

The work and applications we have presented here are transferable to other deserts globally, where annual plant production can be an important component of fuels and where precipitation is highly heterogeneous. In the Monte Desert of Argentina, for example, Mediterranean grass lacks competition from other winter annuals and can accumulate large amounts of biomass following sporadic winter rains (Pucheta *et al.* 2011). The statistical and map-based approaches that we have applied to the Sonoran Desert would be useful to assess the probability of large fires in the Monte Desert, due in part to the introduction of Mediterranean grass. As deserts globally are threatened by ongoing land cover and climate changes, spatial and temporal dynamics in precipitation, fuels and subsequent large fire occurrence will become an increasingly important factor in effective fire planning and management.

Acknowledgements

This research was supported by the US Department of Defense, through the Strategic Environmental Research and Development Program (SERDP; project RC-1722). We thank S. Henry, W. Reaves and A. Alvidres, who provided on-the-ground knowledge of fires and fuels. Members of the Laboratory of Landscape Ecology and Conservation Biology at Northern Arizona University provided useful comments on our approach. We also thank N. Vaillant, A. Olsson and S. Sesnie for their valuable discussions about fuel and fire modelling.

References

Abatzoglou JT, Kolden CA (2011) Climate change in western US deserts: potential for increased wildfire and invasive annual grasses. *Ecology* **64**(5), 471–478.

Abatzoglou JT, Kolden CA (2013) Relationships between climate and macroscale area burned in the western United States. *International Journal of Wildland Fire* **22**(7), 1003–1020. doi:10.1071/WF13019

Allison PD (2012) 'Logistic Regression using SAS: Theory and Application.' (SAS Institute: Cary, NC)

Barbieri MM, Berger JO (2004) Optimal predictive model selection. *Annals of Statistics* **32**(3), 870–897. doi:10.1214/009053604000000238

Bigler C, Kulakowski D, Veblen TT (2005) Multiple disturbance interactions and drought influence fire severity in Rocky Mountain subalpine forests. *Ecology* **86**(11), 3018–3029. doi:10.1890/05-0011

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS (2009) Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in Ecology & Evolution* **24**(3), 127–135. doi:10.1016/J.TREE.2008.10.008

Bradley BA, Blumenthal DM, Wilcove DS, Ziska LH (2010) Predicting plant invasions in an era of global change. *Trends in Ecology & Evolution* **25**(5), 310–318. doi:10.1016/J.TREE.2009.12.003

Brillinger DR, Preisler HK, Benoit JW (2003) Risk assessment: a forest fire example. In 'Science and Statistics: a Festschrift for Terry Speed.' (Ed. D Goldstein) pp. 177–196. (Institute of Mathematical Statistics: Beachwood)

Brooks ML, Chambers JC (2011) Fire and invasive plants special feature: resistance to invasion and resilience to fire in desert shrublands of North America. *Rangeland Ecology and Management* **64**, 431–438. doi:10.2111/REM-D-09-00165.1

Brooks ML, Matchett JR (2006) Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. *Journal of Arid Environments* **67**, 148–164. doi:10.1016/J.JARIDENV.2006.09.027

Brooks ML, Minnich RA (2006) Southeastern deserts bioregion. In 'Fire in California's Ecosystems.' (Eds NG Sugihara, JW van Wagtendonk, KE Shaffer, AE Thode, J Fites-Kaufman) pp. 391–414. (University of California Press: Berkeley, CA)

Brooks ML, Pyke DA (2001) Invasive plants and fire in the deserts of North America. In 'Proceedings of the Invasive Plant Workshop: The Role of Fire in the Control and Spread of Invasive Species.' (Eds K Galley, T Wilson) pp. 1–14. (Tall Timbers Research Station: Tallahassee, FL)

Brown DE (1994) 'Biotic Communities: Southwestern United States and Northwestern Mexico.' (University of Utah Press: Salt Lake City, UT)

Burnham KP, Anderson DR (2002) 'Model Selection and Multimodel Inference: a Practical Information Theoretic Approach.' (Springer: New York)

Casady GM, Van Leeuwen WJ, Reed BC (2013) Estimating winter annual biomass in the Sonoran and Mojave Deserts with satellite- and ground-based observations. *Remote Sensing* **5**, 909–926. doi:10.3390/RS5020909

Crimmins MA, Comrie AC (2004) Interactions between antecedent climate and wildfire variability across south-eastern Arizona. *International Journal of Wildland Fire* **13**, 455–466. doi:10.1071/WF03064

D'Antonio CM (2000) Fire, plant invasions, and global changes. In 'Invasive Species in a Changing World.' (Eds HA Mooney, RJ Hobbs) pp. 65–93. (Island Press: Washington, DC)

D'Antonio CM, Vitousek PM (1992) Biological invasions by exotic grasses, the grass/fire cycle, and global change. *Annual Review of Ecology and Systematics* **23**(1), 63–87.

D'Antonio CM, Chambers JC, Loh R, Tunison JT (2009) Applying ecological concepts to the management of widespread grass invasions. In 'Management of Invasive Weeds.' (Ed RL Inderjit) pp. 123–149. (Springer: Dordrecht, Netherlands)

Dickson BG, Prather JW, Xu Y, Hampton HM, Aumack EN, Sisk TD (2006) Mapping the probability of large fire occurrence in northern Arizona, USA. *Landscape Ecology* **21**(5), 747–761. doi:10.1007/S10980-005-5475-X

Doherty PF, White GC, Burnham KP (2012) Comparison of model building and selection strategies. *Journal fur Ornithologie* **152**, 317–323. doi:10.1007/S10336-010-0598-5

Esque TC, Schwalbe CR (2002) Alien annual grasses and their relationships to fire and biotic change in Sonoran desertscrub. In 'Invasive Exotic Species in the Sonoran Region.' (Ed. B Tellman) pp. 126–146. (Arizona–Sonora Desert Museum and University of Arizona Press: Tucson, AZ)

Esque TC, Webb RH, Wallace CSA, Van Riper C, III, Smythe L (2013) Desert fires fueled by native annual forbs: effects of fire on communities of plants and birds in the lower Sonoran Desert of Arizona. *The Southwestern Naturalist* **58**(2), 223–233. doi:10.1894/0038-4909-58.2.223

Faraway JJ (2006) 'Extending the Linear Model with R: Generalized Linear, Mixed Effects and Nonparametric Regression Models.' (Chapman & Hall and CRC: Boca Raton, FL)

Finney MA, Mchugh CW, Grenfell IC, Riley KL, Short KC (2011) A simulation of probabilistic wildfire risk components for the continental United States. *Stochastic Environmental Research and Risk Assessment* **25**, 973–1000. doi:10.1007/S00477-011-0462-Z

Gillies CS, Hebblewhite M, Nielsen SE, Krawchuk MA, Aldridge CL, Frair JL, Saher DJ, Stevens CE, Jerde CL (2006) Application of random effects to the study of resource selection by animals. *Journal of Animal Ecology* **75**, 887–898. doi:10.1111/J.1365-2656.2006.01106.X

Hawbaker TJ, Radeloff VC, Stewart SI, Hammer RB, Keuler NS, Clayton MK (2013) Human and biophysical influences on fire occurrence in the United States. *Ecological Applications* **23**(3), 565–582. doi:10.1890/12-1816.1

Hijmans RJ, Van Etten J (2012) raster: geographic analysis and modeling with raster data. Available at http://cran.r-project.org/package=raster [Verified 15 August 2014]

Hosmer DW, Lemeshow S (2000) 'Applied Logistic Regression.' (Wiley: New York)

Humphrey RR (1974) Fire in the deserts and desert grassland of North America. 'Fire and Ecosystems.' (Eds TT Kozlowski, CE Ahlgren) pp. 365–401. (Academic Press: New York)

Krawchuk MA, Moritz MA (2011) Constraints on global fire activity vary across a resource gradient. *Ecology* **92**(1), 121–132. doi:10.1890/09-1843.1

Littell JS, McKenzie D, Peterson DL, Westerling AL (2009) Climate and wildfire area burned in western US ecoprovinces, 1916–2003. *Ecological Applications* **19**(4), 1003–1021. doi:10.1890/07-1183.1

Phillips SJ, Comus PW (Eds) (2000) 'A Natural History of the Sonoran Desert.' (Arizona–Sonora Desert Museum Press: Tucson, AZ)

Preisler HK, Brillinger DR, Burgan RE, Benoit JW (2004) Probability based models for estimation of wildfire risk. *International Journal of Wildland Fire* **13**, 133–142. doi:10.1071/WF02061

Preisler HK, Westerling AL, Gebert KM, Munoz-arriola F, Holmes TP (2011) Spatially explicit forecasts of large wildland fire probability and suppression costs for California. *International Journal of Wildland Fire* **20**, 508–517. doi:10.1071/WF09087

Pucheta E, García-Muro VJ, Rolhauser AG, Quevedo-Robledo L (2011) Invasive potential of the winter grass *Schismus barbatus* during the winter season of a predominantly summer-rainfall desert in Central-Northern Monte. *Journal of Arid Environments* **75**(4), 390–393. doi:10.1016/J.JARIDENV.2010.11.010

R Development Core Team (2011) R: A language and environment for statistical computing. Available at http://www.r-project.org/ [Verified 15 August 2014]

Scott JH, Burgan RE (2005) Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. US Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-153. (Fort Collins, CO)

Short, KC (2013) Spatial wildfire occurrence data for the United States, 1992–2011 [FPA_FOD_20130422]. USDA Forest Service, Rocky Mountain Research Station. (Fort Collins, CO) Available at http://dx.doi.org/10.2737/RDS-2013-0009 [Verified 15 August 2014]. doi:10.2737/RDS-2013-0009

Stromberg JC, Hazelton AF, White MS (2009) Plant species richness in ephemeral and perennial reaches of a dryland river. *Biodiversity and Conservation* **18**(3), 663–677. doi:10.1007/S10531-008-9532-Z

Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008) Predicting spatial patterns of fire on a southern

California landscape. *International Journal of Wildland Fire* **17**, 602–613. doi:10.1071/WF07087

Van Linn PF, III, Nussear KE, Esque TC, DeFalco LA, Inman RD, Abella SR (2013) Estimating wildfire risk on a Mojave Desert landscape using remote sensing and field sampling. *International Journal of Wildland Fire* **22**, 770–779. doi:10.1071/WF12158

Vega-García C, Chuvieco E (2006) Applying local measures of spatial heterogeneity to Landsat-TM images for predicting wildfire occurrence in Mediterranean landscapes. *Landscape Ecology* **21**, 595–605. doi:10.1007/S10980-005-4119-5

Venable DL, Pake CE (1999) Population ecology of Sonoran Desert annual plants. In 'Ecology of Sonoran Desert Plants and Plant Communities.' (Ed RH Robichaux) pp. 115–142 (The University of Arizona Press: Tucson, AZ)

Whelan R (1995) 'The Ecology of Fire.' (Cambridge University Press: Cambridge, UK)

Williams RL (2000) A note on robust variance estimation for cluster-correlated data. *Biometrics* **56**, 645–646. doi:10.1111/J.0006-341X.2000.00645.X