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Estimating wildfire risk on a Mojave Desert landscape using remote sensing and field sampling

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Abstract. Predicting wildfires that affect broad landscapes is important for allocating suppression resources and guiding land management. Wildfire prediction in the south-western United States is of specific concern because of the increasing prevalence and severe effects of fire on desert shrublands and the current lack of accurate fire prediction tools. We developed a fire risk model to predict fire occurrence in a north-eastern Mojave Desert landscape. First we developed a spatial model using remote sensing data to predict fuel loads based on field estimates of fuels. We then modelled fire risk (interactions of fuel characteristics and environmental conditions conducive to wildfire) using satellite imagery, our model of fuel loads, and spatial data on ignition potential (lightning strikes and distance to roads), topography (elevation and aspect) and climate (maximum and minimum temperatures). The risk model was developed during a fire year at our study landscape and validated at a nearby landscape; model performance was accurate and similar at both sites. This study demonstrates that remote sensing techniques used in combination with field surveys can accurately predict wildfire risk in the Mojave Desert and may be applicable to other arid and semiarid lands where wildfires are prevalent.

Additional keywords: *Bromus madritensis*, *Bromus tectorum*, desert fire risk modelling, fuel load modelling, Gold Butte, landscape wildfire prediction, *Schismus barbatus*.

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Introduction

Desert ecosystems are characterised by low perennial vegetation cover, low primary productivity, and limited fuel load, which have resulted in deserts historically experiencing fire infrequently (Humphrey 1974; Brooks and Matchett 2006). In the Mojave Desert, non-native annual grasses have invaded during past centuries and have become prevalent in low- and middle-elevation shrublands since a period of high precipitation during 1976 to 1998 (Hunter 1991; Salo 2005; Hereford *et al.* 2006). In recent decades, these annual grasses, including red brome (*Bromus madritensis*), cheatgrass (*B. tectorum*), and common Mediterranean grass (*Schismus barbatus*), have changed the spatial distribution and type of fuels across arid and semiarid landscapes in the south-western USA by creating a continuous fuel bed for fire to spread through naturally large gaps between perennial grasses and shrubs (Brown and Minnich 1986; Brooks 1999). Burnt shrublands are typically recolonised by the exotic grasses that fuelled the fires that burnt them, thus promoting re-burning, a process known as the grass–fire cycle (D'Antonio and Vitousek 1992). Consequently, the frequency, size and intensity of fires in the Mojave Desert have increased concomitantly with increases in fine fuel density (Brooks and Esque 2002; Brooks and Minnich 2006; Esque *et al.* 2010), facilitated by both human and lightning caused ignitions (Brooks and Matchett 2006).

Given the historically infrequent wildfire occurrence in the Mojave Desert in the south-western USA, many plants and animals are poorly adapted to survive landscape-scale fires (Esque *et al.* 2003; DeFalco *et al.* 2010). Adverse effects of fire are of particular concern for land managers because fires can have long-term effects on the structure and species composition of plant communities (Abella 2009; Engel and Abella 2011) and can kill or injure threatened and endangered animal species such as the desert tortoise (*Gopherus agassizii*; Esque *et al.* 2003). However, effects of fire on many Mojave Desert species are largely unknown. Research on fire occurrence and fuel characteristics can expand knowledge of where, when and how desert fires may occur and provide insight for the management of future wildland fires (Loboda 2009). Although several fuel–fire models exist for a variety of ecosystems, fuel load models and fire hazard maps for arid ecosystems, and the Mojave Desert in particular, are lacking (Brooks *et al.* 2004).

Important parameters for modelling potential for desert fires to occur (fire risk) include fuel load, potential ignition sources,

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atmospheric conditions and fuel moisture. Traditionally, fuel inputs for modelling are collected through field experiments and observations aimed at classifying fuels by the rate of fire spread they support, with a focus on designating fire suppression response times (Sandberg *et al.* 2001). These fuel inputs are required for the widely used Rothermel (1972) surface fire spread model and for calculating fuel load, fire danger indices and fire behaviour. Although there are existing efforts to model fire dynamics (e.g. LANDFIRE, http://www.landfire.gov/index.php, accessed 27 November 2012), they frequently suffer from scale issues, where the modelled fuel loads and underlying vegetation community data are derived from large-scale modelling efforts over a variety of ecological systems, and commonly suffer from inaccuracy, especially in arid systems where remote sensing of vegetation is more difficult (Tueller 1987; Okin *et al.* 2001). For example, Mojave Mid-Elevation Mixed Desert Scrub was the least accurately mapped vegetation class in a recent accuracy assessment of LANDFIRE EVT (Stehman 2012). Our objective was to examine fuel characteristics and major fire components of desert systems to create a model of fire risk for a landscape in the north-eastern Mojave Desert. Here, we use the commonly adopted term of fire risk to mean 'the chance for fire to occur, as affected by the nature and incidence of causative agents' (Hardy 2005). Our approach for predicting fire risk included: (1) estimating fuel loadings during 2010 to create a spatial model of fuel throughout the study area based on Normalised Difference Vegetation Index (NDVI), elevation and climate variables that can then be used to predict fuel loads in any given year; (2) combining this spatial model of fuels with remote sensing layers that represent factors that influence wildland fires and their ignition potential (fuel moisture, vegetation type, distance to roads, lightning density) to develop a fire risk model using data from 2005, which was a year of unprecedented fire activity in the Mojave Desert (Brooks and Matchett 2006) and (3) validating our model of wildland fire risk by predicting fire occurrences at a second landscape in 2005 with assessments of model performance comparing predicted *v.* burnt areas.

Methods

Study area

This study was conducted within the 140 928-ha area known as Gold Butte in the north-eastern Mojave Desert of southern Nevada (Fig. 1). Gold Butte is a large block of federal land located 120 km north-east of Las Vegas and managed by the Bureau of Land Management (BLM). Gold Butte is bordered by Lake Mead National Recreation Area to the south and west, the Virgin River to the north and Grand Canyon – Parashant National Monument to the east. Gold Butte serves well as a landscape-scale study area for modelling desert fuels and fire risk because the vegetation communities that comprise the area reflect the variety found across the Mojave as well as in neighbouring deserts. Elevation of the area ranges from 2356 m at Virgin Peak to less than 367 m on the shores of Lake Mead.

Gold Butte is diverse with respect to soils, slope gradient, elevation and aspect. Large outcrops of igneous, sedimentary and metamorphic parent materials dominate the peaks and hill slopes of the Virgin Mountains (Luddington 2007). Parent

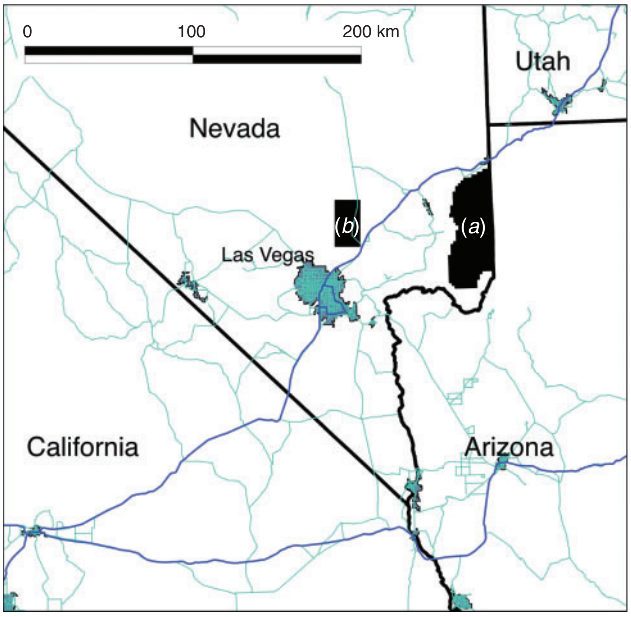

Fig. 1. Map of the Gold Butte study landscape (*a*), and the Coyote Springs Valley validation landscape (*b*) in southern Nevada, USA.

materials produce surface textures ranging from fine clays and aeolian sands through sandy loams, talus and bedrock. Dominant vegetation types by area occupied include: Mojave mixed desert scrub (69%), blackbrush shrublands (24%), and piñon–juniper woodlands (7%). Gold Butte is located in a part of the Mojave Desert that forms a transition zone with three other arid or semiarid ecoregions: the Great Basin Desert, the Sonoran Desert and the Colorado Plateau. This unique convergence results in high floral biodiversity (Bradley 1967) and provides habitat for several threatened species such as the desert tortoise and Las Vegas bearpoppy (*Arctomecon californica*). However, like much of the Mojave Desert, Gold Butte also hosts a variety of exotic annual plants such as red brome, cheatgrass, Mediterranean grass and Sahara mustard (*Brassica tournefortii*), all of which can influence fire regimes by increasing fire spread (Whisenant 1990; Knick and Rotenberry 1997; Brooks and Pyke 2001). In June 2005 lightning started numerous wildfires, collectively called the Southern Nevada Fire Complex, burning over 300 000 ha of Mojave desert habitat, which represented 132% of the total area burnt during the previous 25-year period (Brooks and Matchett 2006). During that fire, ~35 500 ha burnt within Gold Butte.

Fuel load sampling procedures

Fuel loads were estimated on randomly located field survey plots ($n = 252$) within Gold Butte beginning in early spring (April) of 2010 when plants were at peak production (Fig. 1). Fuel loads were surveyed on 30 × 30-m (0.09-ha) plots distributed among 16 different Southwest Regional Gap Analysis Project land cover types (SWReGAP; Lowry *et al.* 2007) and included areas that previously burnt. Within each plot, four 30-m transects were measured for live and dead fuel loads using a modification of the planar intersect method (Brown 1974), which was originally developed to inventory fuel accumulation in forested systems. Survey protocols for forest assessments (Brown 1974; Lutes *et al.* 2006) were integrated with those from fuel assessments in more closely related sagebrush steppe (Stableton and Bunting 2009) to increase sampling efficiency and to focus on the fine fuel types of most concern for desert vegetation. We modified Brown's (1974) planar transects to correspond to the 30-m pixels of the remote sensing layers by using two of four transects centred on the plot, and parallel to one another, with 10 m between them. The second two transects were perpendicular to the first two and also centred on the plot with 10 m between them. At two points along each transect (5 and 25 m) ocular estimates were made within a 2×2-m quadrat (following Lutes *et al.* 2006) of the percent cover of live and dead woody vegetation, live and dead herbaceous vegetation, live and dead woody species average height, live and dead herbaceous species average height, depth of duff and litter profile (i.e. the layers of vegetative fuel debris on the surface above the mineral soil) and the proportion of litter in profile.

Fuels can be categorised by the time required for them to be sufficiently dry to burn, which is related to stem diameter (Pyne *et al.* 1996). This study quantified 1-, 10-, 100-, 1000-, 1–100- and 1–1000-h time-lag fuel loads in 2010 (the latter two being combined classes representing the total fuel loads over the interval). Each transect was divided into three 10-m long segments and randomly assigned one of the three lowest fuel classes (1-, 10- and 100-h time-lag fuels) for quantification. All 30 m of each transect (0–30 m) were used to tally 1000-h time-lag fuels. Additionally, diameter and decay class were recorded for 1000-h time-lag fuels for use in biomass calculations. The number of planar intersects for each time-lag fuel class was tallied as an index of percent cover along the line and used to estimate biomass (kg m^{-2}) of each size class.

Fuel load estimates

Fuel size-class data measured in 2010 were entered into the Fire Effects Monitoring and Inventory Protocol program FIREMON (Lutes *et al.* 2006) to estimate fuel loadings of each sample plot based on fuel size-class tallies, cover of live and dead fuel types (%), average height (m) of live and dead fuel types and duff and litter depths (cm). All fuel-loading estimates were adjusted for slope gradient via FIREMON software and based on Brown (1974). Elevation and slope were attributed to each plot using a Digital Elevation Model (DEM; 10-m resolution; Gesch 2007).

Fuel load model inputs

Parameter-elevation Regressions on Independent Slopes Model (PRISM) monthly precipitation estimates (Daly *et al.* 2002) for the months of October through April were summed to produce one layer depicting winter–spring rainfall. Winter–spring rainfall is a strong indicator of ephemeral plant production in the Mojave Desert (Beatley 1974; Turner and Randall 1989). The 250-m resolution, 16-day NDVI (MOD13Q1; 16-Day L3 Global 250-m data product; Carroll *et al.* 2004), available from the Moderate Resolution Imaging Spectroradiometer (MODIS; ORNL DAAC 2010), was downloaded for the spring and late summer of 2005 and 2010. We used the spring (7–23 April 2005; 9 April–9 May 2010) and summer (28 July–13 August, 2005 and 2010) NDVI greenness indices (respectively SpNDVI and SuNDVI) as measures of live vegetation greenness. Estimates of the ratio of spring and summer NDVI (NDVIrat) and the difference of spring and summer NDVI estimates for each year were calculated according to Wallace and Thomas (2008), using seasonal vegetation measurements rather than annual measurements to focus on the periods of plant production and senescence in the Mojave Desert. Additional data layers depicting topography (elevation, slope gradient and aspect) were calculated from a DEM. Fire history (annual burn perimeters for documented wildfires since 1941) and roads data for Clark County, NV (all known paved and unpaved routes) were provided by the BLM's Southern Nevada District (Las Vegas, Nevada).

Fuel load model

The fuel loading estimates taken at each plot and the potential predictive layers we developed were then used to create a fuel load estimate for the entire study area. To do so, Akaike Information Criterion (AIC) model selection and multi-model averaging (Burnham and Anderson 1998) were used to select among general linear models constructed to relate the fuel loading estimates with combinations of spring NDVI, elevation and maximum and minimum average temperatures (Table 1). We chose to use fuel loads derived from the 1–100-h fuel size classes that we measured in 2010 because they provide the fuel continuity necessary to carry fire among the otherwise spatially isolated heavier fuels of native shrubs and trees. The fuel load model was then used to create a raster of predicted fuel loads for all of Clark County NV encompassing the study area using Eqn 1 at a 250-m grid resolution.

$$\begin{aligned}\text{Fuel load model: estimate fuel} &= 26.218 + 0.0001429 \\ &\times (\text{SpNDVI}) - 0.003 \times (\text{Elev}) - 0.2419 \times (\text{MaxTemp}) \\ &+ 0.014 \times (\text{MinTemp}) + 0.00018 \times (\text{Aspect})\end{aligned} \tag{1}$$

wherein the estimated fuel load (in kg m^{-2}) is for 1–100-h fuels, SpNDVI is the spring NDVI (range of -1 to $+1$), Elev is the elevation (m), MaxTemp and MinTemp are the maximum and corresponding minimum average air temperature from spring to summer, and Aspect is the degrees from true north.

Table 1. Consensus model set for 1–100-h fuels in the north-eastern Mojave Desert, USA

The models accounted for 99% of all model weights and had three variables in common. The averaged model had an R^2 of 0.29. SpNDVI, spring Normalised Difference Vegetation Index (range of -1 to 1 taken on 9 May 2010); Elev, elevation (m); MaxTemp, maximum average temperature; MinTemp, minimum average temperature; Aspect, degrees from true north

Model Term	K	ΔAICc	AICcWt	CumWt
SpNDVI + Elev + MaxTemp	5	0.0	0.42	0.42
SpNDVI + Elev + MaxTemp + Aspect	6	0.3	0.36	0.78
SpNDVI + MinTemp + Elev + MaxTemp	6	1.34	0.21	0.99

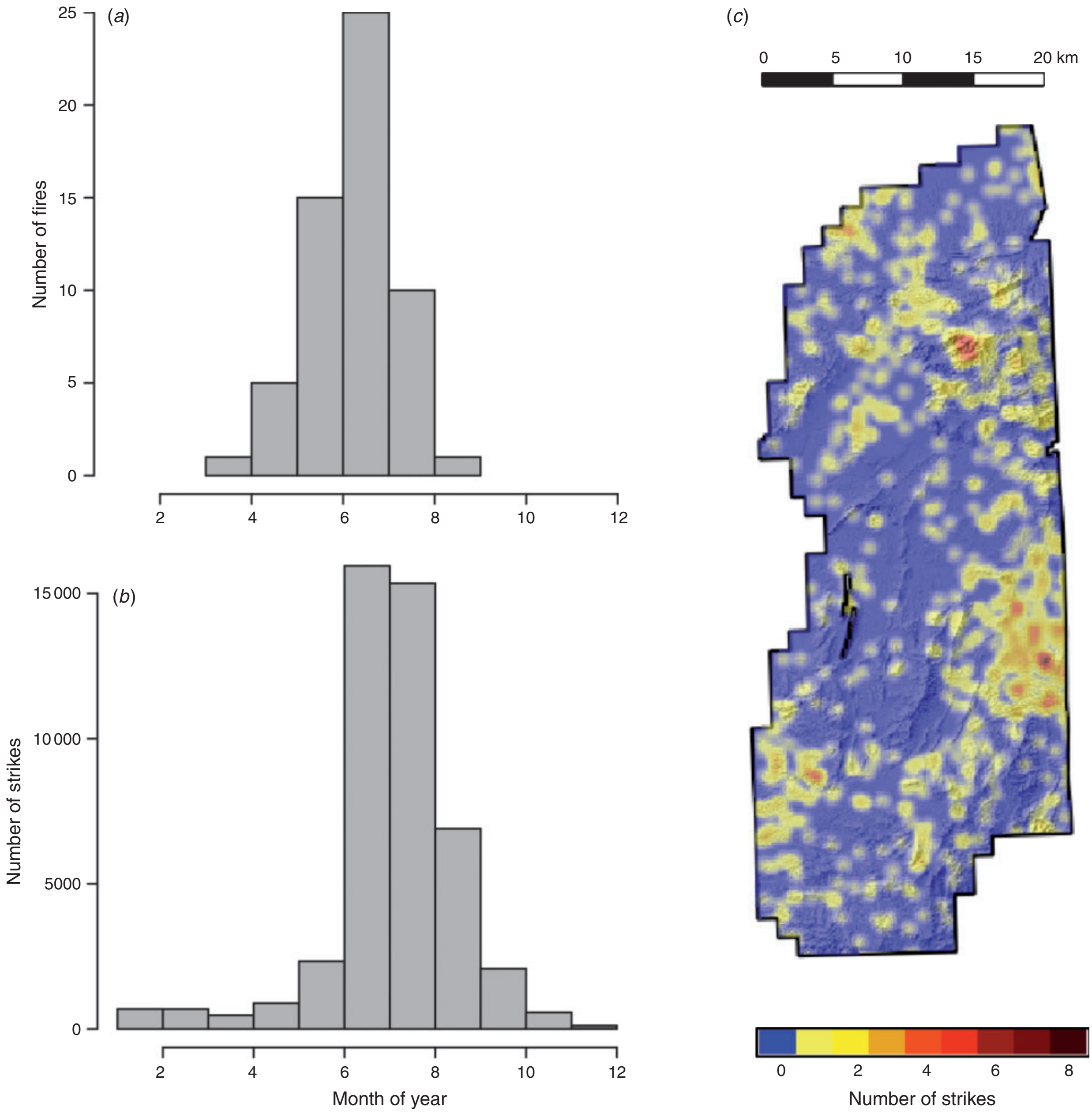

Fig. 2. Frequency of wildland fires by month in Clark County, Nevada (*a*), lightning strike frequency by month in Gold Butte for 10 years (2000–2010; *b*) and the spatial lightning density for June and July of 2005 (*c*).

Fire risk model inputs

Ignition potentials were represented by two sources of data: lightning strike density and distance to roads within the study area. Lightning strike density provides ignition potential for naturally occurring fires, whereas distance to roads represents potential for human-caused ignition (Loboda and Csiszar 2007), which can result from recreational use of the area for camping, shooting and driving off-highway vehicles (Sowmya and Somashekar 2010; Moreno *et al.* 2011). Lightning strike data (2000–2010) for southern NV were obtained from the Desert Research Institute (Reno, NV). Point data depicting lightning were converted to a raster layer in ArcGIS (vers. 9.3, ESRI) using the spatial-analyst density tool. Most lightning strikes in the area occur during June and July, so a lightning density surface was created that combined lightning for June and July of 2005. This time period coincided with extensive fire activity in Gold Butte, and generally in Clark County, NV (Fig. 2). A raster layer depicting distance to the nearest road in Gold Butte was created using GRASS GIS (vers. 6.4; GRASS Development Team 2010).

Fuel moisture content (Fig. 3) was estimated for each 250-m cell using an equation (Eqn 2) adapted from grassland systems (Chuvieco *et al.* 2004), which was chosen because the majority of the fuels in desert ecosystems that carry surface fire are more

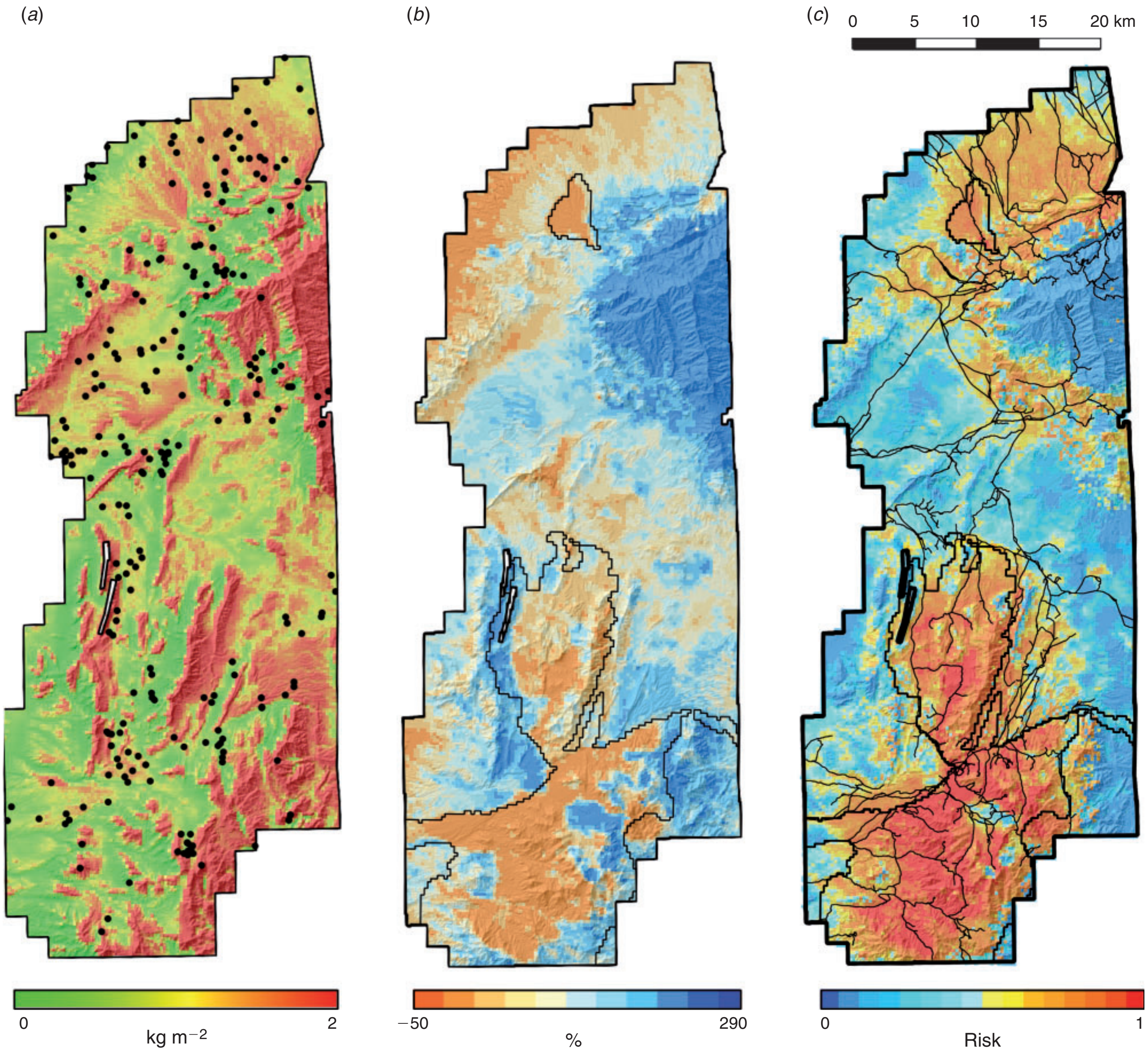

Fig. 3. Spatial depictions of Gold Butte with (*a*) the estimated fuel load with randomly located study plots ($n = 252$) where we measured fuel load estimates indicated by black circles, (*b*) summer fuel moisture estimate, with 2005 fire perimeter indicated by the thin black outline and (*c*) predicted 2005 fire perimeters and roads.

similar to those of grasslands than others available in available models.

$$FMC_g = -57.103 + 284.808 \times NDVI - 0.089 \times ST + 136.75 \times FD_g \quad (2)$$

where FMC_g = fuel moisture content of grasses, ST is the surface temperature (°C), and FD_g is a function of the day of the year given in Eqn 3.

$$FD_g = (\sin(1.5 \times pi \times (Dy + Dy^{1/3})/365))^4 \times 1.3 \quad (3)$$

where Dy is the day of the year.

The fuel moisture content estimates considered both maximum (SM) and minimum (Sm) spring surface temperatures to represent the potential temperature extremes in the region. Vegetation type (V) was determined using a layer of vegetation types developed for the Clark County Nevada Desert conservation program (Heaton *et al.* 2011).

Fire risk model

Potential for fire occurrence in 2005 (fire risk) was modelled using a logistic general linear model in R (v2.12 R Development Core Team 2010). Fire occurrence in 2005 was selected because this was an active fire year for the study area (and the Mojave Desert generally) and few documented fires occurred in the study area before 2005. Fire perimeters from all fires occurring in the study area in 2005 (ArcGIS shapefiles) were converted to a binary raster with a 250-m resolution (using *v*.to.rast in GRASS v6.4), where burnt and unburnt areas were identified separately per raster cell. The input layers described above (distance to roads, summer lightning density, fuel load, fuel moisture content and vegetation type) were then used to determine the best overall model predicting fire occurrence in Gold Butte for 2005. A suite of 118 potential models portraying fire risk using combinations of the input variables were developed and compared using an information theoretic approach (Burnham and Anderson 1998). Because there were ~250 000 cells with 250-m resolution in Gold Butte, 5000 cells were randomly selected for analysis (without replacement within each iteration) to avoid spurious model over fitting. This bootstrapping process was iterated 10 000 times, and competing models were ranked using AIC. The best-fitting model was identified per iteration and coefficients were calculated as the weighted average of their inclusion in the 10 000 best models. The final model estimating fire risk for 2005 was:

$$\begin{aligned}\text{Fire risk in 2005} = {} & \text{D2Roads} + \text{Summer Lightning}\\ & + \text{Summer Fuel Moisture}\\ & + \text{Spring Max Fuel Moisture}\\ & + \text{Fuel load} + \text{Perennial Vegetation type}\\ & + \text{Fuel load} \times \text{Perennial Vegetation type}\\ & + \text{Spring Max Fuel Moisture} \times \text{Fuel load}\\ & + \text{Summer Fuel Moisture} \times \text{Fuel load}\\ & + \text{Spring Max Fuel Moisture}\\ & \times \text{Perennial Vegetation type}\\ & + \text{Summer Fuel Moisture}\\ & \times \text{Perennial Vegetation type}\end{aligned} \tag{4}$$

To evaluate model performance, we calculated receiver operating characteristic (ROC) statistics (area-under-the-curve (AUC)) to determine agreement between model predictions and fire occurrence for 2005 (Elith *et al.* 2006). The ROC curve, which determines sensitivity of the model by plotting the rate of true positives (i.e. prediction of fire occurrence where fire actually occurred) versus false positives (i.e. prediction of fire occurrence when no fire occurred) for each cell in the model, was calculated by comparing the cells estimated to have high fire risk to those cells with known fire occurrence in 2005. AUC statistics of 0.9–1.0 represent sensitive model estimates (Elith *et al.* 2006). We additionally used the model to predict fire risk at a second landscape (21 597-ha within Coyote Springs Valley in Clark County, NV) with similar desert scrubland habitat and evaluated model performance at that location for model validation.

Results

Fuel load estimates

Fuel loads of the 1–100-h time-lag fuel classes ranged from 0 to 0.9 kg m^{-2} and averaged 0.3 among all 252 plots. A fuel load model using multi-model averaging was produced that performed well and was also defensible with respect to ecological interactions thought to drive fuel production (see Eqn 1). The model was most influenced by three of the models considered that comprised the confidence set, accounting for 99% of the weight among all models considered (Table 1).

Fire risk model – 2005

One hundred and eighteen potential fire risk models were analysed for predictive ability using a bootstrap analysis with the best model for each run selected based on AICc (AIC corrected for smaller sample sizes). The same model was selected as the best in each of the 10 000 bootstrap analyses predicting fire occurrence in Gold Butte for 2005. This model included both of our surrogates for ignition (distance to roads and lightning density), the modelled fuel loading, estimates of maximum spring and summer fuel moisture and the perennial vegetation type. Several important interactions were also included (see Eqn 4). Fuel load interacted with the associated perennial vegetation type and both estimates of fuel moisture, which could indicate differential fuel loadings produced among the different vegetation types. The fuel moisture estimates also interacted with the perennial vegetation type, which could indicate differential susceptibility of vegetation types to ignition under similar fuel moistures. The model had an AUC of 0.88 indicating that for 2005 the fire risk model accurately predicted fire occurrence (Fig. 4). The performance of the model at the validation site was similar, with an AUC of 0.85 (Fig. 4).

A comparison of the fire risk prediction model for 2005 (Fig. 3*c*) with the fuel loading map and fuel moisture map (Fig. 3*a*, *b*) illustrates that areas of low to moderate fuel loading and moderate fuel moisture content were predicted to have the highest risk of fire. Furthermore, a large proportion of the area predicted to have a high fire risk in 2005 actually burnt (20 040 ha of 25 403 at risk = 0.79, Fig. 3*c*). Another smaller area in the northern region of Gold Butte that burnt in 2005 was not predicted to have a high fire risk (10 107 ha; Fig. 3*c*). Despite greatest fuel loading at higher elevations on the Virgin Mountains, these areas actually had low fire risk due to much higher and more continuous fuel moisture in that area (Fig. 3*a*, *b*). The validation site, although smaller in area, showed similar correspondence between the predicted fire risk and the area burnt in 2005 (Fig. 5). Again, there were a few areas of higher risk that did not burn likely because they were segregated from either ignition or spread, or could have been saved by fire suppression crews that were actively fighting the fire as it moved northward.

Discussion

Our fuel load and fire risk modelling techniques performed well in a desert environment where fuel load characteristics are highly variable and difficult to predict because of the spatial heterogeneity of the factors driving the system. The fuel load model described ~29% of the variability in fuel loads, and this study showed that fire risk could be predicted with reasonably high accuracy. However, a large amount of unexplained variation remained in the fuel load models. This variation may be attributed to the low representation of areas with high fuel loads in the models, or to the generally high variability in fuel load characteristics in desert vegetation due to their patchy

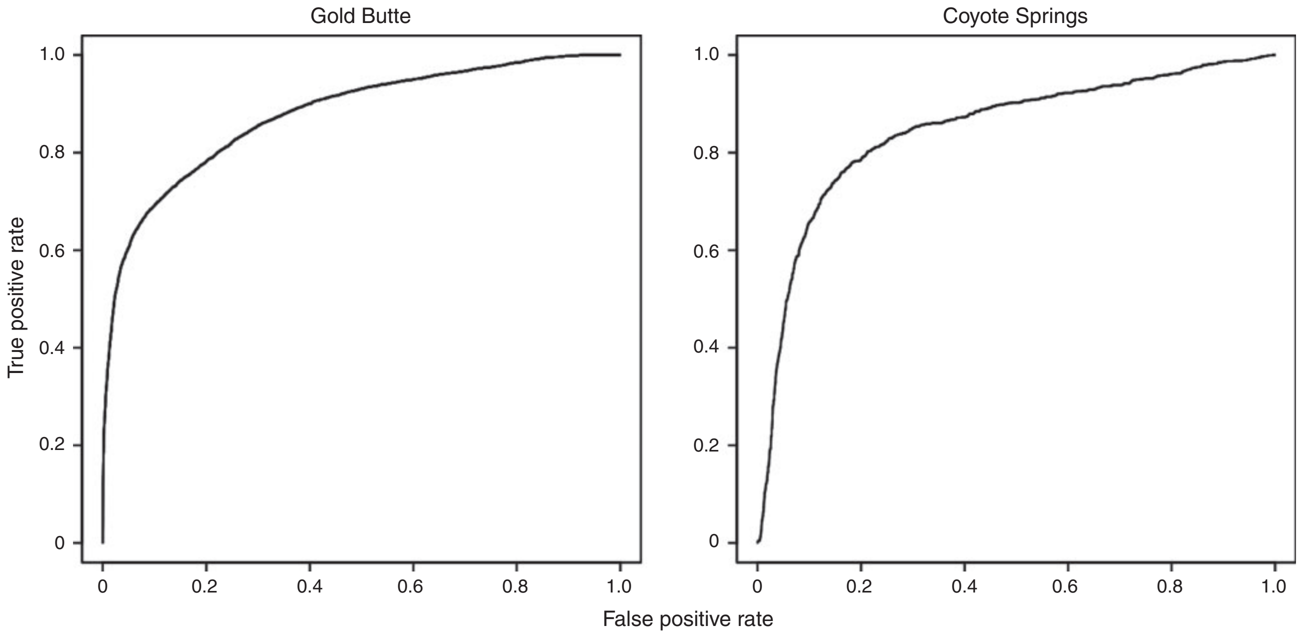

Fig. 4. ROC curves used to evaluate the performance of the fire risk model at Gold Butte (left AUC = 0.88), and Coyote Springs Valley (right, AUC = 0.85).

distribution (Allen 2001). Some of the unexplained variation may also be due to the wide range of fuel types that occur in Gold Butte that were incorporated into our models. Our study focussed on the entire area within Gold Butte; however, we expect that modelling a smaller subset of vegetation types, such as desert shrublands and excluding areas with extreme fuel loads (woodlands and barren rock outcrops), could reduce the variance in the fuel model. Another way to increase fuel model accuracy might be to match the field sampling as closely as possible to the remote sensing units (Miller and Yool 2002) or to examine the interspace and below-shrub microsites typifying desert vegetation for fuel load and fire behaviour characteristics. It is important to note that the fuel load models developed for this study were not directly linked to fuel load models commonly used for forest fire research (Albini 1976; Deeming *et al.* 1977; Anderson 1982), although remote sensing techniques are increasingly being used for fuel load assessment and fire risk prediction in arid ecosystems (Chen *et al.* 2011).

The fuel loadings we used are accurate for dense perennial grasslands (e.g. Konza Prairie, Kansas, Chuvieco *et al.* 2004), and we expected fuels of grasslands to better represent the desert shrubland fuel loads that are modified by increased fuel continuity contributed by exotic grasses. However, the fuels found in desert shrublands of the Mojave Desert are qualitatively and quantitatively different from prairie grasslands due to the high spatial variability of fuel loads, fuel geometry and total fuel loads. For instance, windblown seeds of annual grasses are captured by perennial shrubs and grow more densely beneath their canopies where soil nutrients are concentrated (Walker *et al.* 2001). In addition, prairie grass species are active (green) throughout the summer unlike Mojave Desert exotic grass species, which are active during spring and senesce during the summer. Further fuels modelling focussed on common western desert fuel types may benefit fire risk modelling endeavours. Fuel models that focus on the lower bajada and alluvial fan Mojavean–Sonoran desert scrub merged with the Mojave upper desert scrub groups may improve predictions of fire risk in south-western desert landscapes.

In addition to our fuel model, we used remote sensing data to represent other important characteristics of fire risk (e.g. NDVI, potential ignition sources, fuel moisture content and temperatures). Consequently, we produced a model that depicts fire risk for the entire study landscape, which has promise as a management tool (Loboda 2009; Chen *et al.* 2011). This tool or variations of it may be applied to other areas of the Mojave Desert and has potential for other desert ecoregions where exotic grasses have become prevalent (Pucheta *et al.* 2011) or where frequent large desert fires have caused long-term effects on natural lands and native species (Gill *et al.* 1981; Pyne 1991). Our model clearly identified areas of high fire risk and can be used to frame future research objectives. Our fire risk model for 2005 was successful at predicting where risk was high and fires actually occurred as well as areas that had low risk and did not burn, at both the model development and the validation sites. We also noted areas where fire did not occur but were predicted to have a high fire risk. We think that these false positives indicate areas that had high potential for fire but did not have an ignition source and coincide with accumulations of fine fuels across consecutive years at low and middle elevations in the Mojave Desert (Brooks and Matchett 2006).

Procedures described in this study could be used to predict fire risk in future years, and these predictions could be strengthened with additional field validation during peak annual plant production between April and May of the target year (Beatley 1974). These data would only provide ~1-month advance notice of fire risk before the onset of the fire season (typically

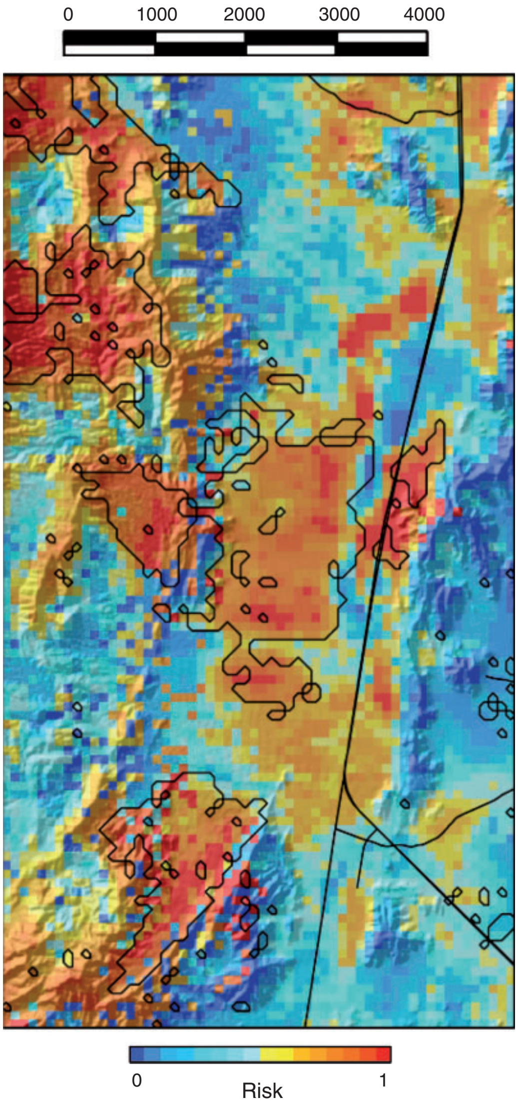

Fig. 5. Fire risk (indicated by blue (low) to increasing red (high) coloration) relative to the 2005 burn perimeter at the Coyote Springs Valley, Nevada, validation site.

in June), but identification of areas having consistently high fire risk from year to year could be a significant benefit (Loboda 2009). It is clear that expanding the temporal predictive window of fire risk would enhance the ability of managers to assemble equipment and other resources in response to the predicted fire risk. Our research provides a better alternative to current large-scale modelling efforts by providing locally calibrated fuel load and fire risk modelling that can be used by land managers in south-western arid lands. Increasing the temporal prediction window will require accurate availability of fine-scale precipitation data across landscapes (higher resolution than now available) and a better understanding of the relationship between the amount and timing of rainfall and temperature in relation to fuel development. Developing an antecedent model to predict annual plant biomass ahead of annual plant growth would provide land managers with more forewarning of high fire risk in areas of concern.

Our fuel load models successfully demonstrated the potential to use remote sensing data in combination with field surveys for estimating fuel loads across a Mojave Desert landscape. This synthesis of techniques presents a cost-saving method for estimating fuel loads across landscapes that have not previously had fuel and fire risk models widely available. Field estimation of fuel loading is costly and logistically difficult (Miller and Yool 2002), and refinement of techniques that can reduce the amount of field sampling necessary while focussing on modelling components may further increase effectiveness by improving on the framework presented here.

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References

Abella SR (2009) Post-fire plant recovery in the Mojave and Sonoran Deserts of western North America. *Journal of Arid Environments* **73**, 699–707. doi:10.1016/J.JARIDENV.2009.03.003

Albini FA (1976) Estimating wildfire behavior and effects. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-030. (Ogden, UT)

Allen EB (2001) Temporal and spatial organization of desert plant communities. In 'Semiarid Lands and Deserts: Soil Resource and Reclamation'. (Ed. J Skujiņš) pp. 193–208. (Marcel Dekker Inc.: New York)

Anderson HE (1982) Aids to determining fuel models for estimating fire behavior. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-122. (Ogden, UT)

Beatley JC (1974) Phenological events and their environmental triggers in Mojave Desert ecosystems. *Ecology* **55**, 856–863. doi:10.2307/1934421

Bradley WG (1967) A geographical analysis of the flora of Clark County, Nevada. *Journal of the Arizona Academy of Science* **4**, 151–162. doi:10.2307/40022399

Brooks ML (1999) Alien annual grasses and fire in the Mojave Desert. *Madrono* **46**, 13–19.

Brooks ML, Esque TC (2002) Alien plants and fire in desert tortoise (*Gopherus agassizii*) habitat in the Mojave and Colorado deserts. *Chelonian Conservation and Biology* **4**, 330–340.

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 Schaffer, J Fites-Kaufman, AE Thode) pp. 391–414. (University of California Press: Berkeley, CA)

Brooks ML, Pyke D (2001) Invasive plants and fire in the deserts of North America. In 'The Role of Fire in the Control and Spread of Invasive Species. Fire Conference 2000: The First National Congress on Fire Ecology, Prevention and Management: Conference Proceedings', 27 November–1 December 2000, San Diego, CA. (Eds KEM Galley, TP Wilson) Tall Timbers Research Station Miscellaneous Publication Number 11, pp. 1–14. (Tallahassee, FL)

Brooks ML, Matchett JR, Wallace C, Esque TC (2004) Fuels mapping and fire hazard assessment in a desert ecosystem. *Arid Lands Newsletter*, **55**, May–June 2004. Available at http://ag.arizona.edu/oals/ALN/aln55/brooks.html [Verified 13 February 2013]

Brown JK (1974) Handbook for inventorying downed woody material. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-16. (Ogden, UT)

Brown DE, Minnich RA (1986) Fire and creosote bush scrub of the western Sonoran Desert. *American Midland Naturalist* **116**, 411–422. doi:10.2307/2425750

Burnham KP, Anderson DR (1998) 'Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach.' (Spring Science and Business Media: New York)

Carroll ML, DiMiceli CM, Sohlberg RA, Townshend JRG (2004) 250 m MODIS normalized difference vegetation index data product. (The Global Land Cover Facility) Available at http://glcf.umiacs.umd.edu/data/modis/ndvi/ [Verified 13 February 2013]

Chen F, Weber KT, Anderson J, Gokhal B (2011) Assessing the susceptibility of semiarid rangelands to wildfires using Terra MODIS and Landsat Thematic Mapper data. *International Journal of Wildland Fire* **20**, 690–701. doi:10.1071/WF10001

Chuvieco E, Cocero D, Riaño D, Martin P, Martinez-Vega J, de la Riva J, Pérez F (2004) Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sensing of Environment* **92**, 322–331. doi:10.1016/J.RSE.2004.01.019

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**, 63–87.

Daly C, Kittel T, Nychka D, Johns C, Rosenbloom N, McNab A, Taylor G (2002) Development of a 103-year high-resolution climate data set for the conterminous United States. A report to NOAA Climate Change Data and Detection Program. Available at http://www.prism.oregonstate.edu/pub/prism/docs/noaa02-finalreport-daly.doc [Verified 13 February 2013]

Deeming JE, Burgan RE, Cohen JD (1977) The National Fire-Danger Rating System-1978. USDA Forest Service, Intermountain Research Station, General Technical Report INT-39. (Ogden, UT)

DeFalco LA, Esque TC, Scoles-Sciulla SJ, Rodgers J (2010) Desert wildfire and severe drought diminish survivorship of the long-lived Joshua tree (*Yucca brevifolia; Agavaceae*). *American Journal of Botany* **97**, 243–250. doi:10.3732/AJB.0900032

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S, Guisan A, Hijmans RJ, Huettmann F, Leathwick JR, Lehmann A, Li J, Lohmann LG, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton JM, Peterson AT, Phillips SJ, Richardson K, Scachetti-Pereira R, Schapire RE, Soberón J, Williams S, Wisz MS, Zimmermann NE (2006) Novel methods improve predictions of species' distributions from occurrence data. *Ecography* **29**, 129–151. doi:10.1111/J.2006.0906-7590.04596.X

Engel EC, Abella SR (2011) Vegetation recovery in a desert landscape after wildfire: influences of community type, time since fire and contingency effects. *Journal of Applied Ecology* **48**, 1401–1410. doi:10.1111/J.1365-2664.2011.02057.X

Esque TC, Schwalbe CR, DeFalco LA, Duncan RB, Hughes TJ (2003) Effects of wildfire on desert tortoise (*Gopherus agassizii*) and other small vertebrates. *The Southwestern Naturalist* **48**, 103–111. doi:10.1894/0038-4909(2003)048<0103:EODWOD>2.0.CO;2

Esque TC, Young JA, Tracy CR (2010) Short-term effects of experimental fires on a Mojave Desert seed bank. *Journal of Arid Environments* **74**, 1302–1308. doi:10.1016/J.JARIDENV.2010.04.011

Gesch DB (2007) The National Elevation Dataset. In 'Digital Elevation Model Technologies and Applications: The DEM Users Manual.' 2nd edn. (Ed D Maune) pp. 99–118. (American Society for Photogrammetry and Remote Sensing: Bethesda, MD)

Gill AM, Groves RH, Noble IR (Eds) (1981) 'Fire and the Australian Biota.' (Australian Academy of Science: Canberra)

GRASS Development Team (2010) Geographic Resources Analysis Support System (GRASS) Software, Version 6.4.0 (Open Source Geospatial Foundation) Available at http://grass.osgeo.org [Verified 13 February 2013]

Hardy CC (2005) Wildland fire hazard and risk: problems, definitions, and context. *Forest Ecology and Management* **211**, 73–82. doi:10.1016/J.FORECO.2005.01.029

Heaton JS, Miao X, Von Seckendorff Hoff K, Charlet D, Cashman P, Trexler J, Grimmer A, Patil R (2011). Final Report 2005-UNR-578. University of Nevada Reno, Report to Clark County MSHCP 2005-UNR-578:D27. (Reno, NV) Available at http://www.clarkcountynv.gov/depts/dcp/Pages/DCPReports.aspx [Verified 13 February 2013]

Hereford R, Webb RH, Longpré CI (2006) Precipitation history and ecosystem response to multidecadal precipitation variability in the Mojave Desert region, 1893–2001. *Journal of Arid Environments* **67**, 13–34. doi:10.1016/J.JARIDENV.2006.09.019

Humphrey RR (1974) Fire in the deserts and desert grassland of North America. In 'Fire and Ecosystems'. (Eds TT Kozlowski, CE Ahlgren) pp. 365–400. (Academic Press: New York)

Hunter R (1991) *Bromus* invasions on the Nevada Test Site: present status of *B. rubens* and *B. tectorum* with notes on their relationship to disturbance and altitude. *The Great Basin Naturalist* **51**, 176–182.

Knick ST, Rotenberry JT (1997) Landscape characteristics of disturbed shrubsteppe habitats in southwestern Idaho. *Landscape Ecology* **12**, 287–297. doi:10.1023/A:1007915408590

Loboda TV (2009) Modeling fire danger in data-poor regions: a case study from the Russian Far East. *International Journal of Wildland Fire* **18**, 19–35. doi:10.1071/WF07094

Loboda TV, Csiszar IA (2007) Assessing the risk of ignition in the Russian far east within a modeling framework of fire threat. *Ecological Applications* **17**, 791–805. doi:10.1890/05-1476

Lowry J, Ramsey RD, Thomas K, Schrupp D, Sajwaj T, Kirby J, Waller E, Schrader S, Falzarano S, Langs L, Manis G, Wallace C, Schulz K, Comer P, Pohs K, Reith W, Velasquez C, Wolk B, Kepner W, Boykin K, O'Brien K, Bradford D, Thompson B, Prior-Magee J (2007) Mapping moderate-scale land-cover over very large geographic areas within a collaborative framework: a case study of the Southwest Regional Gap Analysis Project (SWReGAP). *Remote Sensing of Environment* **108**, 59–73. doi:10.1016/J.RSE.2006.11.008

Luddington S (Ed.) (2007) Mineral resource assessment of selected areas in Clark and Nye Counties, Nevada. United States Geological Survey, Scientific Investigations Report 2006–5197. (Menlo Park, CA) Available at http://pubs.usgs.gov/sir/2006/5197/[Verified 13 February 2013]

Lutes DC, Keane RE, Caratti JF, Key CH, Benson NC, Sutherland S, Gangi LJ (2006) FIREMON: Fire effects monitoring and inventory system. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-164. (Fort Collins, CO)

Miller JD, Yool SR (2002) Modeling fire in semi-desert grassland/oak woodland: the spatial implications. *Journal of Arid Environments* **153**, 229–245.

Moreno JM, Viedma O, Zavala G, Luna B (2011) Landscape variables influencing forest fires in central Spain. *International Journal of Wildland Fire* **20**, 678–689. doi:10.1071/WF10005

ORNL DAAC (2010) MODIS Land Product Subsets, Collection 5. (Oak Ridge National Laboratory Distributed Active Archive Center) Available at http://daac.ornl.gov/MODIS/modis.html [Verified 13 February 2013]

Okin GS, Roberts DA, Murray B, Okin WJ (2001) Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments. *Remote Sensing of Environment* **77**, 212–225. doi:10.1016/S0034-4257(01)00207-3

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**, 390–393. doi:10.1016/J.JARIDENV.2010.11.010

Pyne SJ (1991) 'Burning Bush: a Fire History of Australia.' (Henry Holt and Company, Inc.: New York)

Pyne SJ, Andrews PL, Lavern RD (1996) 'Introduction to the Wildland Fire.' (Wiley: New York)

R Development Core Team (2010). 'The R project for statistical computing'. Available at http://www.R-project.org/ [Verified 13 February 2013]

Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service, Intermountain Forest and Range Experiment Station, Research Paper INT-115. (Ogden, UT)

Salo L (2005) Red brome (*Bromus rubens* subsp. *madritensis*) in North America: possible modes for early introductions, subsequent spread. *Biological Invasions* **7**, 165–180. doi:10.1007/S10530-004-8979-4

Sandberg DV, Ottmar RD, Cushon GH (2001) Characterizing fuels in the 21st Century. *International Journal of Wildland Fire* **10**, 381–387. doi:10.1071/WF01036

Sowmya SV, Somashekar RK (2010) Application of remote sensing and geographical information system in mapping forest fire risk zone at Bhadra Wildlife Sanctuary, India. *Journal of Environmental Biology* **31**, 969–974.

Stableton A, Bunting S (2009) Guide for quantifying fuels in the sagebrush steppe and juniper woodlands of the Great Basin. Bureau of Land Management, Technical Note 430. (Denver, CO)

Stehman S (2012) Landfire accuracy estimates for the Great Basin Superzone: comparison of original estimates with poststratified estimates adjusted for the proportion of area in each EVT Map class. Available at http://www.landfire.gov/downloadfile.php?file=Stehman-LF_Analysis_Feb8.pdf [Verified 20 September 2012]

Tueller PT (1987) Remote sensing science applications in arid environments. *Remote Sensing of Environment* **23**, 143–154. doi:10.1016/0034-4257(87)90034-4

Turner FB, Randall DC (1989) Net productivity by shrubs and winter annuals in southern Nevada. *Journal of Arid Environments* **17**, 23–36.

Walker LR, Thompson DB, Landau FH (2001) Experimental manipulations of fertile islands and nurse plant effects in the Mojave Desert, USA. *Western North American Naturalist* **61**, 25–35.

Wallace CSA, Thomas KA (2008) An annual plant growth proxy in the Mojave Desert using MODIS-EVI Data. *Sensors* **8**, 7792–7808. doi:10.3390/S8127792

Whisenant SG (1990) Changing fire frequencies on Idaho's Snake River plains: ecological and management implications. In 'Cheatgrass Invasion, Shrub Die-Off, and Other Aspects of Shrub Biology and Management: Conference Proceedings', 5–7 April 1989, Las Vegas, NV. (Eds ED McArthur, EM Romney, SD Smith, PT Tueller) USDA Forest Service, Intermountain Research Station, General Technical Report INT-276, pp. 4–10. (Ogden, UT)