LANDSCAPE-SCALE MODELS AND MAPS OF FIRE RISK AND CONNECTIVITY IN THE LOWER SONORAN DESERT

By Miranda E. Gray

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Approved:
Brett Dickson, Ph.D., Chair
Peter Fulé, Ph.D.
Thomas Sisk, Ph.D.

ABSTRACT

Landscape-Scale Models and Maps of Fire Risk
and Connectivity in the Lower Sonoran Desert

Miranda Gray

In the lower Sonoran Desert of southwestern Arizona, heterogeneity in the amount and location of precipitation can result in extreme inter-annual fluctuations in fine fuel accumulations. Coupled with ongoing climate change and invasion by non-native grasses and forbs, this pattern has the potential to contribute to more frequent and larger fires that were historically uncommon. Where sparse vegetation and mild weather one year might regulate the frequency and spread of fire, contiguous beds of plant biomass and anomalous weather the next year can spread fire across large extents. Appropriate fire management in this region will require an improved understanding of landscape-scale fire risk under variable climatic and fuel conditions, as well as the implications of increased large fire likelihood. Generalized linear mixed modeling is used to estimate the relative contributions of fuel attributes (e.g., loading and configuration), landscape characteristics, and human infrastructure to large fire risk. These results suggest that inter-annual fluctuations in large fire risk can be captured with a variable of the maximum annual Normalized Difference Vegetation Index (NDVI). To account for the contagious property of fire, a connectivity model is used to estimate where on the landscape fire is likely to burn, under high risk conditions. Coupled with an *a priori* knowledge of the factors that influence fire resiliency, these results identify areas on the landscape that contribute most to the high consequence of fire likelihood, which can help inform fire management across broad scales and multiple jurisdictions.

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1.0 Introduction

Before 1970 wildfire was not considered an important element of community change in the Sonoran Desert (Esque and Schwalbe 2002). With the increase in abundance of invasive grasses that are capable of starting and carrying fires very long distances, wildfire is now a serious concern in a system adapted to small and infrequent fires (Abatzoglou and Kolden 2011). Non-native grasses respond more favorably to frequent fire than do native desert plants and eventually propagate what is known as the grass/fire cycle, which reduces abundance of native plants and increases the abundance of non-native plants (D'Antonio and Vitousek 1992). Although the potential for rapid and dramatic change due to the invasive grass/fire cycle is well appreciated, little work has been devoted to understanding fire patterns in the lower Sonoran Desert, which would help inform management policy. This research applies landscape connectivity methods to evaluate landscape-scale patterns of fire likelihood (e.g. the likelihood of a site burning based on landscape characteristics, accumulation of fine fuels, etc) in the lower Sonoran Desert of southwestern Arizona.

Deserts tend to experience less fire than other ecosystems due to limited production of fuels, therefore little research has been committed to desert fires. It is recognized that landscape-scale models of fire need to be expanded to a broader spectrum of ecosystem types and climatic zones (Gardner et al. 1999). In the Sonoran Desert of the southwestern US, there is concern that climate change and land use activities are increasing fire risk through establishment and spread of non-native, fire adapted grasses and forbs, including African buffelgrass (*Pennisetum ciliare*), red brome (*Bromus rubens*), Sahara mustard (*Brassica tournefortii*), and Mediterranean grass (*Schismus* *arabicus and S. barbatus*). Because precipitation and temperature significantly influence plant habitat suitability, climate change is likely to alter the distribution of these species (Brown 1994). The plants might also expand dramatically in response to land use activities (Bradley et al. 2010).

Heterogeneity in precipitation in the Sonoran Desert can result in extreme inter-annual fluctuations of fuel accumulation (Crimmins and Comrie 2004). Large, uncharacteristic wildfires in dry seasons are thought to be primarily fueled and spread by contiguous beds of non-native plant biomass following years of very high precipitation (Swetnam and Betancourt 1998). On the other hand, in 2005 a 10,000 hectare fire was carried primarily by a native plant following one of the wettest periods recently recorded in southwestern Arizona (Webb et al. 2007). These conditions illustrate the pressing need to understand the overall contributions of fuel, landscape and climatic variables to fire disturbance in this region.

Connectivity as an ecological concept is most often applied in conservation biology to assess the dispersal capabilities of individuals and genes among populations and generations (Rayfield et al. 2011). Robust connectivity is acknowledged as critical to maintaining viable populations and as a result there is extensive literature devoted to the appropriate choice of connectivity models, for the specific species or process under study (Urban and Keitt 2001, McRae et al. 2008, Pinto and Keitt 2008). Fire is a fundamentally different process than animal dispersal and interacts with the terrain to define the unique functional connectivity of a landscape. In this context, functional connectivity determines landscape conductance to fire, or the ability of the landscape to facilitate the spread of fire.

A connectivity model of fire disturbance describes coarse spatial and temporal scale processes, and makes simplified assumptions about, for example, the fine-scale processes of fire spread. Fire prediction models currently emphasize the fine-scale dynamics of fire behavior with the purpose of understanding fire events over the length of a single fire. The models, commonly called mechanistic simulation models (Finney 1999), deterministically simulate the spread of fire based on detailed thermodynamics and the physical and chemical characteristics of fuels (e.g. Albini 1976, Finney 2004, Peterson et al. 2009). A different approach to fire behavior modeling captures broader scale patterns with a probabilistic model of fire spread (e.g. Clarke et al. 1994, He and Mladenoff 1999, Hargrove et al. 2000). A connectivity model is most similar to these models; the propagation from one cell to another is not based on physical laws but rather it is probabilistic and depends on the amount of accumulated fuel, weather, terrain, etc.

1.1 Research objectives and hypotheses

The specific objectives of my research were to:

(1) Use a generalized linear mixed modeling (GLMM) approach to estimate and map large fire risk in the lower Sonoran Desert of southwestern Arizona

H_{R1}: Inter-annual shifts in large fire risk can be captured with a variable representing the annual maximum Normalized Difference Vegetation Index (NDVI), coupled with a variable representing antecedent precipitation and landscape variables.

(2) Parameterize a conductance surface for fire spread for input into a circuit-theoretic model of connectivity, such that the environmental factors and

component processes thought to contribute most to large-sale patterns are accounted for and accurately characterize fire spread probabilities.

H$_{R2}$: Borrowing methods from landscape connectivity, the individual and synergistic influence of fuels, landscape characteristics, and weather on large fire risk can be extrapolated to fire likelihood that accounts for fire spread.

(3) Derive a model of fire connectivity for a heterogeneous landscape in the lower Sonoran Desert of southwestern Arizona.

H$_{R3}$: A fire connectivity model can identify specific areas on the landscape through which fire has the highest likelihood of passing.

The threat of an invasive grass/fire cycle in the lower Sonoran Desert calls for an implementable landscape-scale approach to fire modeling that gives fire managers a tool to mitigate rapid and dramatic changes to this diverse ecosystem. Because fire threatens desert ecosystems worldwide, my research can contribute to rigorous and contemporary efforts to understand desert fire regimes.

The following two chapters are written as co-authored articles to be submitted to peer-reviewed journals, and as a result some redundancy will appear between the two chapters. Chapter 2 addresses objective (1) of my research, while chapter 3 addresses objectives (2) and (3) of my research.

2.0 Modeling and mapping dynamic variability in large fire risk in the lower Sonoran Desert of southwestern Arizona

2.1 Introduction

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 characterize 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 resiliency (Brooks and Chambers 2011). These disruptions can lead to alternative stable states of herbaceous cover 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). Recurrent fires that collectively homogenize vegetation over large areas are also detrimental to native animal species of concern, including the Sonoran desert tortoise (*Gopherus morafkai*) and endangered Sonoran pronghorn (*Antilocapra americana sonoriensis*) (Esque et al. 2002, Hervert et al. 2005).

Increased fire activity in desert regions depends predominantly on antecedent soil moisture to stimulate vegetative growth (Krawchuck and Moritz 2011). In systems where fine fuels control the spread of fire, the globally consistent strength of antecedent moisture correlations demonstrates that up to two years of above-normal precipitation can drastically change fuel loads and the propensity of an area to burn (Littell et al. 2009, Krawchuck and Mortiz 2011). These climate-driven increases in fuel can be accompanied by very large increases in inter-annual and spatial variability of large fire occurrence (Brooks and Matchett 2006, Littell et al. 2009). Ignition sources and continuity of fuels in a given year are two factors that influence this variability (Littell et al. 2009). Large fire risk, which is the chance that a fire ignition might become a spreading fire due to natural and human factors, provides a probabilistic concept for fire management (Hardy 2005). Although large fires only represent a small number of all fires, they account for most of the burned area (Meyn et al. 2007). By identifying areas of large fire risk, managers would be able to better design and coordinate adaptive fire management strategies.

In arid ecosystems, statistically robust estimates of annual large fire risk need to account for the high levels of inter-annual variation in precipitation and fuel factors that typically precede a fire event. Previous modeling studies in arid and semiarid environments have shown the utility of the Normalized Difference Vegetation Index (NDVI) to estimate dynamic fuel conditions and fire risk at a regional extent (Russell-Smith et al. 2007, Turner et al. 2011). These and other studies have reported the separate effect of drought and rainfall indices on fire occurrence (Preisler et al. 2011). However, antecedent precipitation and fuels presumably act together to influence fire risk, and this synergism may differentially influence other landscape variables. Thus, it is necessary to account for the effect of antecedent precipitation on large fire risk in a way that can be integrated with highly dynamic fuel conditions and landscape information. Primarily as a consequence of human activities and the prevalence of invasive plant species, more than 70,000 ha of the lower Sonoran desert of southwestern Arizona have burned since 2000, with most (> 75%) of this area burning in 2005. In light of these events, there have been no published fire studies in this region to inform how land managers might monitor large fire risk and adapt to dynamic changes in the environment. Managers in the region are particularly concerned about the establishment of non-native, fire adapted grasses and forbs, including red brome (*Bromus rubens*), Mediterranean grass (*Schismus arabicus* and *S. barbatus*), African buffelgrass (*Pennisetum ciliare*), and Sahara mustard (*Brassica tournefortii*). Poorly planned land use or restoration efforts could further benefit invasive plant species, if they do not account for the anticipated impacts of climate variability and change (Bradley et al. 2010).

The objectives of our research were to model and map large fire risk across the lower Sonoran desert in southwestern Arizona and to apply an improved understanding of dynamic fire risk to recommendations for the management of fire in the region. Specifically, we sought to: (1) couple the interaction between precipitation and fuel conditions by deriving estimates of the maximum annual NDVI for 1989-2010 from satellite imagery; (2) incorporate these estimates of NDVI into a probability-based statistical model of large (≥ 20 ha) fire risk that simultaneously considered antecedent precipitation and the influence other environmental variables; (3) extend this model to produce high spatial resolution (i.e., 30 m) and up-to-date maps of dynamic large fire risk across multiple jurisdictions; and (4) use these results to explore patterns of fire risk, and inform future management activities concerned with mitigating the individual or synergistic impacts of fire and non-native plant invasion in Sonoran desert lowlands.

2.2 Methods

2.2.1 Study area

The 45,100-km^2 study area is located in southwestern Arizona, USA, and encompasses multiple jurisdictions that include vast areas of Bureau of Land Management land, the U.S. Army Yuma Proving Ground (3,360 km^2), the Barry M. Goldwater Air Force Range (7,070 km^2), as well as the Kofa (2,690 km^2; KNWR) and Cabeza Prieta National Wildlife Refuges (3,468 km^2) (Fig. 2.1). Mean elevation is 372 m (SD = 182 m) and ranges from 26 m in the southwestern lowlands to 1,480 m on the KNWR. Lower elevations (< 600 m) on the study area are comprised primarily of the Lower Colorado subdivision of the Sonoran desert (Brown 1994). This subdivision is among the most arid of the North American deserts and is characterized by sparsely vegetated desert shrublands dominated by Creosote bush (*Larrea tridentata*) and White bursage (*Ambrosia dumosa*) (Phillips and Comus 2000). 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 (Dec.) 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 mm and 92 mm, respectively, falls as winter precipitation. The winter of 2004-2005 was particularly wet for this region, recording more than 300 percent of the average winter precipitation across the study extent (Western Regional Climate Center 2009, www.wrcc.dri.edu). These wet years, coupled with historical land use (e.g., agricultural) activities, have facilitated increased invasion by non-native invasive plants (Brooks and Pyke 2001).

2.2.2 Fire occurrence data

We compiled fire occurrence data from two databases that included natural and human-caused point ignitions on both federal and non-federal lands (Short 2013, Fire Program Analysis, http://www.fpa.nifc.gov/)

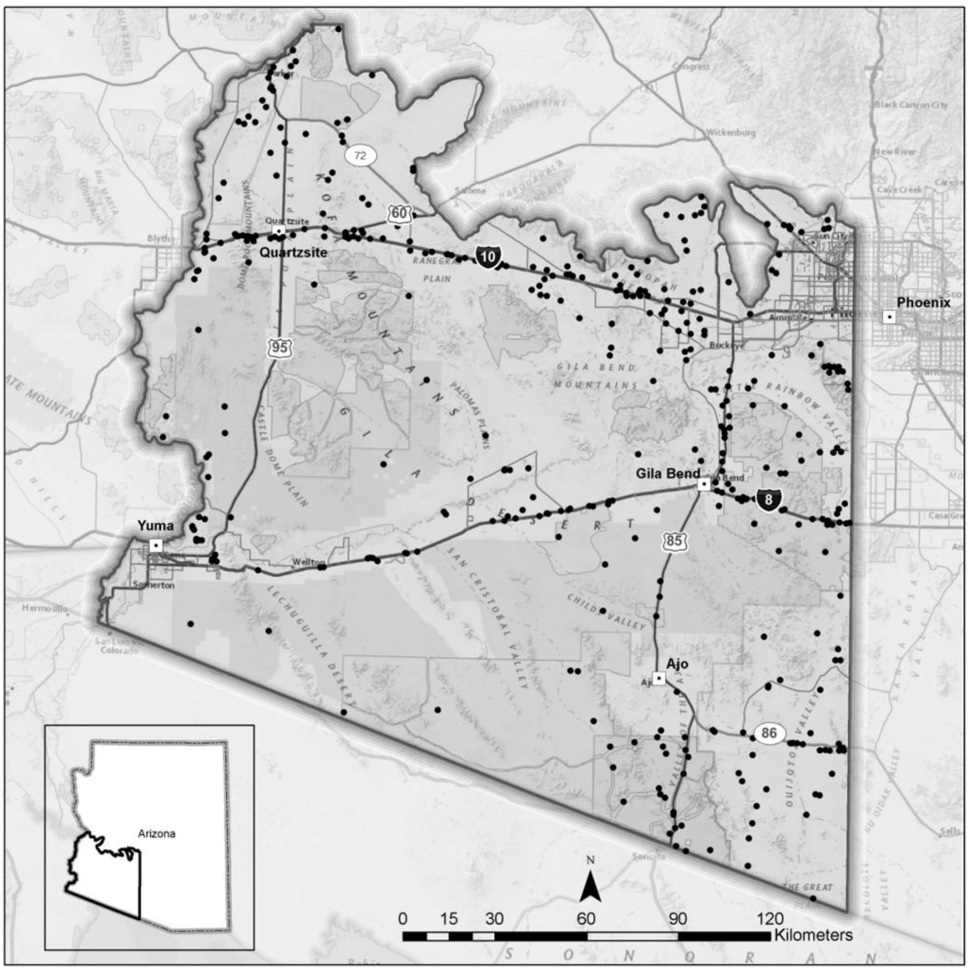

Fig. 2.1 The 45,100-km^2 study area used to model fire risk in the lower Sonoran Desert of southwestern Arizona, 1989-2010. Black dots represent large (≥ 20 ha) fire ignition points recorded during the period 1989-2010.

We used records from the period 1989-2010 that included the latitude and longitude of the point of origin, date of ignition, and total area burned. Using a Geographic Information System (GIS; ArcGIS v10.1, Esri, Redlands, CA), we extracted information on all large (≥ 20 ha) fires that burned during the study period. 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 (Wade Reaves BLM, personal communication). We used the GIS to convert our final occurrence dataset to a shapefile and related these data to modeled variables prior to statistical analysis.

2.2.3 Landscape variables

We accounted for the direct effect of fine fuel loads on large fire probability using a time-series analysis and derivatives of the NDVI. Yearly maximum NDVI is a measure of vegetation greenness derived from satellite imagery, which can be used as a proxy for annual fuel accumulations (Turner et al. 2011). The index also provides a spatially and temporally dynamic variable for estimating fire risk over extensive areas (Maselli et al. 2003). To estimate yearly maximum NDVI values for 1988-2010, coincident with our fire occurrence database, we obtained Landsat Thematic Mapper 5 scenes for five path/rows covering our study area (n = 1114) from the U.S. Geological Survey (USGS) Global Visualization Viewer (http://glovis.usgs.gov), and atmospherically corrected all images using ENVI software (v4.7, Exelis Visual Information Solutions). Our model included variables of the year-of-fire maximum NDVI value as well as the maximum

NDVI value of the year prior to the fire year. The lagged year variable accounts for senesced biomass that can remain standing as fuel for two subsequent fire seasons.

Within the GIS, we derived a NDVI-based variable to represent the horizontal spatial structure of perennial fuels. Previous research in the Mediterranean region of Spain used Landsat TM to relate fire hazard to the horizontal distribution of vegetation (Vega-García and Chuvieco 2006). Those results indicated that a locally repeating vegetation signal, or in other words homogeneity of fuels, favors the spread of fire. We considered this result in the context of far-reaching, homogenous shrublands in the Sonoran Desert, which can amass continuous extents of fine fuels and similarly favor the spread of fire. Thus, our variable for horizontal fuel structure was the standard deviation of maximum NDVI in 1989, representing fuel heterogeneity at the beginning of our analysis period.

Our modeling 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 U.S. Geological Survey (http://ned.usgs.gov/) , we derived estimates of elevation, aspect (in degrees), and terrain roughness (standard deviation of mean 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. Therefore, we used the GIS and US Census Bureau TIGER line data (2011; www.census.gov/geo/www/tiger) to estimate a simple road density (in km/km^2) variable that could serve as a proxy for human accessibility and help to differentiate where fires are more or less likely to become large.

All variables were derived as or converted to raster grids with a 30-m pixel resolution. We computed mean or standard deviation focal statistics for each variable using a moving window operation in the GIS and a 15×15-pixel neighborhood. We used the Raster package in the R statistical environment (v2.15.1; www.r-project.org) to extract environmental variables from each point ignition. Prior to implementing our statistical model, we standardized and rescaled values of all continuous landscape variables to a mean of zero and unit variance.

2.2.4 Statistical and spatial modeling

We used mixed-effects logistic regression to estimate the probability of a large fire, given a natural or human caused ignition event, and conditioned on the seven environmental variables (i.e., fixed effects) described above. The binary response in this model was an ignition event that resulted in a large fire ('1') or that did not grow larger than 20 ha ('0'), resulting in a 'small' fire. A random sample of small fires 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). This sampling scheme increased the ratio of ones to zeros without biasing the coefficient estimates (Syphard et al. 2008, Allison 2012).

We included the immediate winter growing season precipitation anomaly and one lag season precipitation anomaly as crossed random effects. By including these variables as random effects, available moisture variability was identified explicitly and the scope of inference can be extended to any given year within a 22-year period (Gillies et al.

2006). This also allowed us to merge the dynamic precipitation variables with vegetation indices (i.e., time-series NDVI) without confounding the two effects, and provide more robust estimates of the fixed effect parameters (Faraway 2006). Precipitation anomalies, based on 1981-2010 normals, were derived from 800-m gridded data as the percent of normal precipitation from October through March (Western Regional Climate Center; http://www.wrcc.dri.edu/monitor/WWDT/archive.php). For parsimony, and to account for the variance associated with winter precipitation totals, we categorized each random effect into five quantiles.

To account for spatial autocorrelation 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 the estimator to compute the variance-covariance matrix of the fixed effect parameters.

We used an information-theoretic approach and multi-model inference to identify and contrast explanatory variables within a 'full' model that included all seven fixed effects and two random effects (Burnham and Anderson 2002). We used maximum likelihood to estimate model-averaged regression coefficients for our fixed effects ($\tilde{\tilde{\beta}}$) and Akaike's Information Criterion (AIC), to derive robust estimates that accommodate model selection uncertainty (Burnham and Anderson 2002). We computed AIC weights to rank and evaluate the weight of evidence in favor of a fixed-effect variable given all possible models combinations (Burnham and Anderson 2002). We summed the AIC weights across all models in which a given variable (j) occurred and considered a cumulative AIC weight ($w_+(j)$) ≥ 0.50 to be strong evidence for a response (i.e., probability of a large fire) 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 the Hosmer-Lemeshow statistic to evaluate goodness of fit (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 within the SAS and R Statistical Programming environments (GLIMMIX procedure in SAS v9.2, SAS Institute, Cary, North Carolina, USA; and R Statistical Package v2.15.1).

We used model-averaged regression coefficients and a GIS to implement the full model and produce a probabilistic, spatially explicit response surface for two analysis years, 1996 and 2005, at a 30-m pixel resolution. We chose these years to illustrate dynamic risk in a moderate fine-fuel scenario (1996) and high fine-fuel scenario (2005), and we refer to the maps as moderate and high fire risk scenarios, respectively. 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).

2.3 Results

2.3.1 Fire occurrence

Our final dataset included 316 'small' fires and 79 'large' fires that burned between 1989 and 2010 across the study area. Over these 21 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 average size of a large fire in 2005 was 1,436 ha (SD = 4,178), whereas the 21-year average size of a large fire was 712 ha (2,910). 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. 2.2).

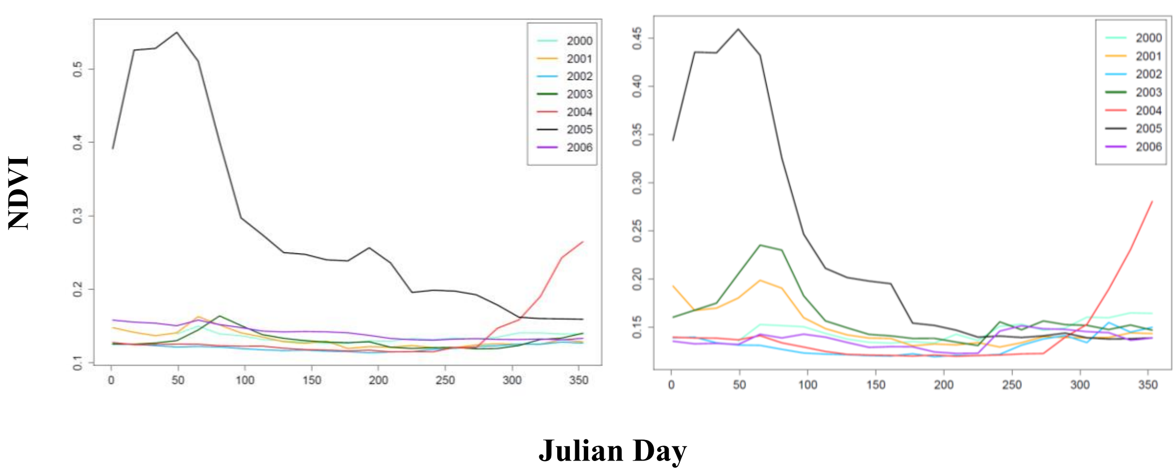

Fig. 2.2 Trends in NDVI from 2000-2006 within the perimeter of two large fire events. The King Valley fire (left) burned in Septemer-October 2005, and the Goldwater fire (right) burned in June 2005.

2.3.2 Statistical and spatial modeling

Our full model of large fire risk, including all seven environmental variables, was 71 ΔAIC units lower (i.e., better) than a null model containing only the random effects.

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 good discrimination. Among the environmental variables we evaluated, areas with relatively 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 risk of large fire (Table 2.1). Low vegetation (fuel) 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 environmental variables we considered.

Table 2.1 Environmental variables (fixed effects) used to estimate large fire risk in the lower Sonoran Desert of southwestern Arizona, 1989-2010.

Cumulative Akaike's Information Criterion (AIC) weights ($w_+(j)$), model-averaged regression coefficients ($\tilde{\tilde{\beta}}$), and unconditional standard errors (SE) were estimated using all possible subsets (n = 128) of the full model.

Variable (i)	$w_+(j)$	$\tilde{\tilde{\beta}}$	SE
Maximum annual NDVI	1.000	0.047	0.008
Road density	1.000	-0.974	0.238
Elevation	1.000	-0.958	0.223
Fuel heterogeneity	0.903	-0.742	0.425
Aspect (northness)	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 2.2 Best linear unbiased predictors of random effects used to estimate large fire risk in the lower Sonoran Desert of southwest Arizona, 1989-2010.
Levels of the random effects represent the precipitation anomaly in the winter season immediately prior to fire season (*i*) or in the one lag-year winter season (*j*).

Level	PON[A]	γ_i [B]
(*i*)		
1	4.4 - 43.3	0.210
2	43.3 - 91.7	-0.384
3	91.7 - 163.0	-0.162
4	163.0 - 238.0	0.595
5	238.0 - 324.0	-0.201
(*j*)		
1	7.3 - 54.3	-0.607
2	54.3 - 81.2	0.132
3	81.2 - 141.0	0.579
4	141.0 - 191.0	0.020
5	191.0 - 314.0	-0.060

[A] Percent of normal precipitation based on 1981-2010 normals
[B] Best linear unbiased predictor

The random effects ranged from below ten percent to above 300 percent of normal winter precipitation (Table 2.2). The best linear unbiased predictors for the random effects revealed that precipitation anomaly in the two antecedent seasons had quite different effects on the probability of large fire. Maps of the high (2005; Fig. 2.3) and moderate fire risk (1996; Fig. 2.4) 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 risk (e.g. > 60 percent) (Fig. 2.4), whereas in 2005 very high risk was much more widespread and spatially contiguous (Fig. 2.3). Considering the entire study area, the mean probability of large fire was 0.37 (SD = 0.21) and 0.13 (0.08) in 2005 and 1996, respectively.

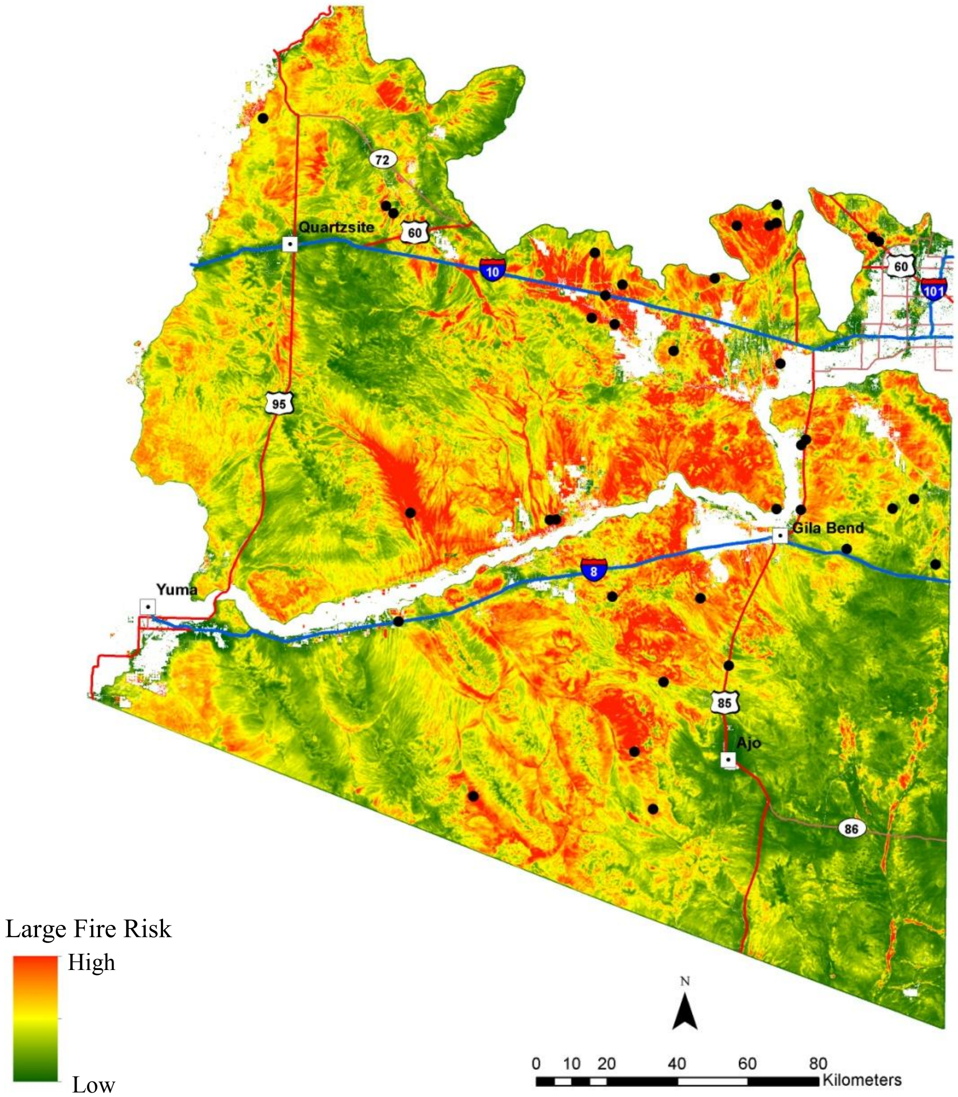

Fig. 2.3 Map-based result for estimate of large fire risk in the lower Sonoran Desert of southwestern Arizona, based on 2005 conditions (i.e., high fire risk). The ignition point of large (≥20 ha) fires that burned in 2005 are represented by black dots.

2.4 Discussion

When exposed to fire sizes and frequencies outside of their historical range of variability, desert ecosystems with a low resiliency to fire are especially susceptible to an alternative, fire-promoting stable state dominated by invasive plant species (D'Antonio et al. 2009). In hot desert shrublands, resilience to fire and resistance to alternative states tends to decrease down an elevation and productivity gradient, where fires have

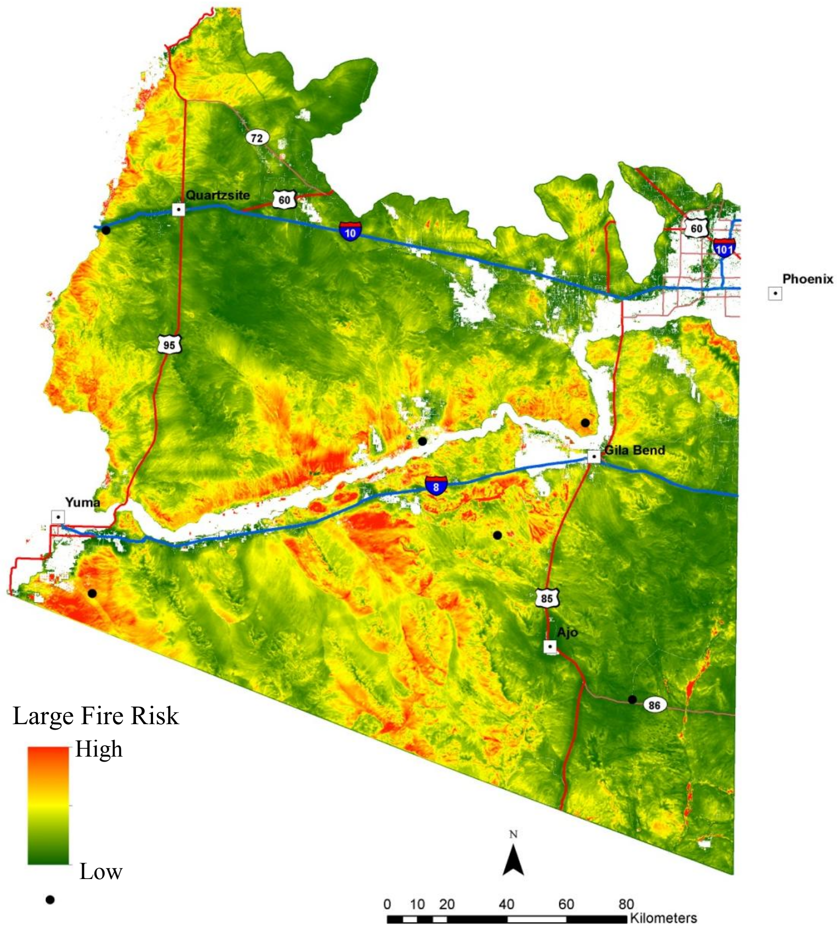

Fig. 2.4 Map-based result for estimate of large fire risk in the lower Sonoran Desert of southwest Arizona, based on 1996 conditions (i.e., moderate fire risk). The ignition point of large (≥20 ha) fires that burned in 1996 are represented by black dots.

historically been the least frequent (Brooks and Chambers 2011). This predisposes the lowest elevations of the Sonoran Desert to rapid environmental change. In the face of ongoing climate and land cover changes, our results provide a timely assessment that can be used to help deter negative consequences of large fire events in the lower Sonoran desert.

Our results show that the important synergism between antecedent precipitation and fuel growth can be integrated into models and maps of large fire risk. Since the exact effects of precipitation on fuel growth and fire risk can be unpredictable, the random effects in our models captured low-level variation in risk over time. Perhaps not surprisingly, our results indicated that areas of high fire risk fluctuate over time and are strongly influenced by values for annual maximum NDVI. After high rainfall years, significant increases in fine fuels that contribute to large fire risk 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*) fueled a large fire event in 2005 (Webb et al. 2007). Nevertheless, because non-native plants played a co-dominant role in fueling the fires of 2005, they highlight the importance of monitoring the overall response of grasses and forbs to heavy precipitation. Recent invasions by non-native annual plants have introduced novel fuel conditions and may act to amplify fire-climate relationships in the Sonoran desert region (Esque and Schwalbe 2002). Mediterranean grass, for example, given its tolerance for extreme drought, is one of the few annuals capable of proliferating in this harsh and changing environment and has 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, > 1 m wide, and is a prolific seed producer (Brooks and Minnich 2006).

Our results suggested that areas of lower elevation, which generally comprise the Lower Colorado subdivision, are at higher risk of large fire than adjacent uplands in the study area. These areas are also expected to exhibit lower fire resiliency, and 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 m and 600 m. Repeated fire events in low elevation areas has great potential to initiate an invasive grass/fire cycle and homogenize vegetation over large areas (D'Antonio and Vitousek 1992).

We found fire risk to be highest in areas of low road density, which we attribute primarily to difficult access for fire suppression (Syphard et al. 2008). Fire spread rates typically are highest in grass and shrubland fuels and can quickly grow larger in more remote regions (Scott and Burgan 2005). Indeed, our study region is comprised of 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 U.S. Army Yuma Proving Ground and quickly spread to the adjacent Kofa wilderness. The 11,000 ha Growler Peak fire spread mostly in the less frequented areas of the Barry M. Goldwater Range.

Our results showed that some of the most common communities of native perennial vegetation in our study area might be especially prone to large fires. For example, risk was highest in more uniform distributions of vegetation across the landscape, as indicated by similar maximum 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). These relatively homogenous communities are subject to accumulations of fine fuel in their interspaces and may facilitate ignitions becoming large fires.

We found that south facing aspects, which face the direction of prevailing winds out of the south and southwest, facilitated small fires becoming large. The maximum effect of weather, topography, and fuel on fire spread occurs when wind direction is directly aligned with aspect (Whelan 1995). At the same time, south facing aspects tend to be more arid and drier environments for vegetation. Thus, the effects of aspect on spreading fire fronts and on fuel characteristics and flammability likely combine to influence large fire risk.

High values for maximum NDVI in the year prior to large fire occurrence demonstrated that annual plants might remain available to fuel large fires for at least two consecutive fire seasons. This pattern may become even more important with changing fuel conditions and composition, for example, given that Mediterranean grass tends 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. The availability of high spatial and high temporal resolution satellite imagery (e.g., Landsat TM) permits the practical integration of NDVI patterns into risk forecasting.

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 risk 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. 2008) (Fig. 2.4). Changes in xeroriparian plant communities can affect an array of ecosystem functions provided by these important microhabitats, and uncharacteristic fire should be considered a potential stressor (Stromberg et al. 2008).

2.4.1 Conclusions and management implications

Our modeling approach and associated map products can be used to monitor and mitigate fire risk, and can help land and resource managers to maintain landscape resiliency to fire and resistance to extensive invasion by non-native plants. As a means of monitoring the risk of large and potentially damaging fire events, we recommend applying monitoring efforts to specific locations for risk mitigation. This might mean that management is first prioritized based on an *a priori* understanding of the ecological conditions that influence ecosystem resilience and resistance (Brooks and Chambers 2011). For instance, managers can use modeled habitat of non-native plants to determine where fire risk might exacerbate the potential for an invasive/fire cycle (Olsson et al. in review). Our results could, in turn, be used to focus mitigation efforts on areas of high fire risk, to curb ignition potential or to prioritize fuel treatments on the landscape. Since fire is primarily limited by the amount of fuel rather than fire season weather, fuel treatments in high risk areas could reduce the vulnerability and increase the fire resilience of native Sonoran vegetation communities.

Managers should also be alert to increased variability in winter precipitation ahead of the spring and summer periods, when fires are most likely to ignite (Abatzoglou and Kolden 2011). Effective management of fire should consider the temporal dynamics of climate and fuels, as demonstrated by our models of moderate and high risk scenarios. Most of the landscape features related to large fire occurrence can be thought of as environmentally stable factors that show unchanging geographical variations in fire risk. However, distinct differences in inter-annual risk are captured with simple NDVI metrics integrated with landscape characteristics. Near-term spatial monitoring tools are manifest in seasonal or annual maps of large fire risk. These fire risk maps also can provide spatially explicit, monitoring locations for proximate land management jurisdictions. Risk that transmits across jurisdictional boundaries can introduce *ex situ* risk, and should encourage managers to coordinate their fire and fuel management objectives. Over the long-term, modeling results should be reevaluated to incorporate more years of comprehensive fire data and maintain the scope of inference for up-to-date management (Brooks and Matchett 2006). As desert fire regimes are threatened by ongoing land cover and climate changes, temporal dynamics will become an increasingly important factor in fire planning and management.

3.0 Analyzing fire likelihood with landscape-scale models and maps of fire connectivity in the lower Sonoran Desert of southwestern Arizona

3.1 Introduction

Landscape-scale analyses of fire risk are critical when anomalously large, stand-replacing wildfires are destabilizing whole ecosystems (Pausas and Keeley 2009). Strategic planning for ecosystem resilience to large fires requires an *a priori* understanding of where on the landscape fire is likely to burn (fire likelihood) and with what consequence to valued resources (fire impacts) (Miller and Ager 2013). Indeed, estimating fire likelihood and impacts at scales relevant to ecosystems may be the most challenging part of fully communicating fire risk for management (Ager et al. 2012). In this chapter we present a circuit theoretic model of fire connectivity as a novel approach to estimate fire likelihood, which we use to explore fire impacts in support of strategic planning across large landscapes.

As a contagious process, the spatial context of fire is extremely important in predicting whether a particular location is likely to burn (Miller and Ager 2013). A network, which is a collection of nodes and edges interacting as a system, provides a means to explore the role of spatial context in influencing contagion (Proulx et al. 2005). Mathematical approaches to analyze the behavior of networks, such as graph and circuit theory, have been widely used in ecology to measure landscape connectivity (e.g., Urban and Keitt 2001, McRae et al. 2008). Landscape connectivity is "the degree to which the landscape facilitates or impedes movement (of a process) among resource patches" (Taylor et al. 1993). Landscape network measures typically emphasize how routes between resource patches, and the topological properties of patches, contribute to overall connectivity (Calabrese and Fagan 2004, Rayfield et al. 2011). In this paper we shift the emphasis to overall landscape conductance, i.e. the ability of the landscape to facilitate the spread of fire.

Circuit theory provides a rigorous mathematical framework that has greatly improved understanding of how landscape characteristics influence the flow of ecological processes across large landscapes (McRae and Beier 2007, McRae et al. 2008). Connectivity models based on circuit theory, or 'current flow' models, are concerned with the blind, undirected movement of an entity (e.g., an animal, fire) across an underlying conductive surface (i.e., a network that conducts current) (Carroll et al. 2011). In contrast to deterministic movement, in which fire would take the 'best' route to a predetermined target, fire moving through a circuit network acts like random walkers that have no knowledge of the landscape beyond their immediate neighbors (Borgatti 2005). The resultant circuit-theoretic predictions provide concrete ecological interpretations, which can be used to identify landscape features through which fire has a high likelihood of passing (McRae et al. 2008). Current flow models can be run easily and efficiently on very large landscapes (e.g. > 1 million cells) and are robust to changing scale (McRae et al. 2008).

Understanding the spatiotemporal dynamics of fire likelihood is critical in the desert shrublands of North America, where fire frequency and size have historically been low (Brooks and Pyke 2001). Increased fire activity due to global climate and land cover changes has potential to catalyze the conversion of native shrublands into grasslands, threatening the loss of habitat for sensitive animal species and alteration to surface hydrology (Brooks and Chambers 2011, Balch et al. 2013). While fire at any intensity level is of concern, the impact of fire to ecological resources is influenced by the heterogeneity inherent in deserts, based on dominant patterns of net primary productivity, vegetation types, precipitation, or other ecological gradients (Crimmins and Comrie 2004, Brooks and Matchett 2006, Balch et al. 2013). Fire impacts are relative to the amount of fire that an area can withstand before new alternative states establish, known as fire resiliency (Brooks and Chambers 2011). The spatiotemporal relationships between fire likelihood and fire impacts can be used to explore wildfire exposure across ecological resources and management jurisdictions (Ager et al. 2012).

The objectives of our research were to model and map fire likelihood and fire impacts across much of the lower Sonoran Desert in southwestern Arizona, and to demonstrate their application in a spatial management framework to advance strategic wildland fire planning. Specifically, we sought to: (1) parameterize a conductance surface for fire spread accounting for environmental factors and component processes that contribute to large fire occurrence, and that accurately characterize fire spread probabilities under high risk conditions; (2) use the conductance surface to produce a current flow model of fire likelihood, and translate categorized outputs to a map of high fire likelihood; (3) produce a map of predicted fire impacts based on knowledge of fire resiliency in the lower Sonoran Desert; and (4) demonstrate how estimates of fire likelihood can be coupled with expected fire impact in a spatial management framework.

3.2 Methods

3.2.1 Modeling fire likelihood as current flow

The underlying networks in current flow models are analogous to electrical circuits and are defined by a graph structure of interconnected nodes and resistors that conduct current (McRae et al. 2008). The strength of a resistor (i.e., its resistance, or inversely, conductance) reflects the probability of movement between its incident nodes, thereby setting up the model as a probabilistic analysis of flow (Carroll et al. 2011). Whole contiguous landscapes can be modeled as circuit networks by representing landscape grid cells as nodes connected by resistors (Rayfield et al. 2011). When an ecological flow originates from a source node and randomly moves through the network until it reaches a target node, circuit theory equates the likelihood of flow passing through any intermediate node to the current density. In the following paragraph, we describe how these general current flow and landscape connectivity methods can be applied to estimates of fire likelihood that account for fire spread.

Models built from historical fire data can be used to create continuous maps of large fire occurrence, or risk (i.e., probability of an ignition becoming larger than some size threshold; Preisler & Westerling, 2007). While this method accounts for large fire originating from an isolated location, it does not account for spread dynamics, for example, to adjacent grid cells in a raster, and is therefore limited in its capacity to predict whether a particular location is going to burn (Thompson and Calkin 2011). A current flow model treats the risk of large fire as one parameter in the conductance of the landscape to fire spread. Additional spatial controls on fire spread that are not accounted for in a risk model, such as the local variability of wind direction and speed, can be incorporated as additional conductance parameters. Therefore, conductance is proportional to the probability of the landscape sustaining a large fire and reflects additional costs to fire spread. As the landscape is now an interconnected network, the current flow model accounts for spread to adjacent cells. Conductance can be defined according to and tested for the region under study, so as to reflect the regional importance of spatial controls on fire spread.

3.2.2 Study area

The 45,100-km^2 study area is located in southwestern Arizona, USA (Fig. 3.1). The study area includes the U.S. Army Yuma Proving Ground (YPG; 3,360 km^2) and the Barry M. Goldwater Air Force Range (BMGR; 7,070 km^2), the two largest military installations in Arizona, as well as the Kofa (KNWR; 2,690 km^2) and the Cabeza Prieta National Wildlife Refuges (CPNWR; 3,468 km^2), two of the largest U.S. Fish and Wildlife Service National Wildlife Refuges in the continental United States, and the Organ Pipe Cactus (OPCNM; 1,335 km^2) and Sonoran Desert National Monuments (SDNM; 1,971 km^2). The study area encompasses multiple land-management jurisdictions, important levels of ecosystem heterogeneity, and contiguous expanses of native habitats affected by large-scale fire and non-native plant invasion.

The mean elevation of the study area is 372 m, and ranges from < 100 m on the western lowlands of the BMGR to nearly 1500 m on the KNWR. Numerous small mountain ranges are separated by expansive desert valleys, plains and bajadas that typify the Lower Colorado subdivision of the Sonoran Desert (Brown 1994). Portions of the

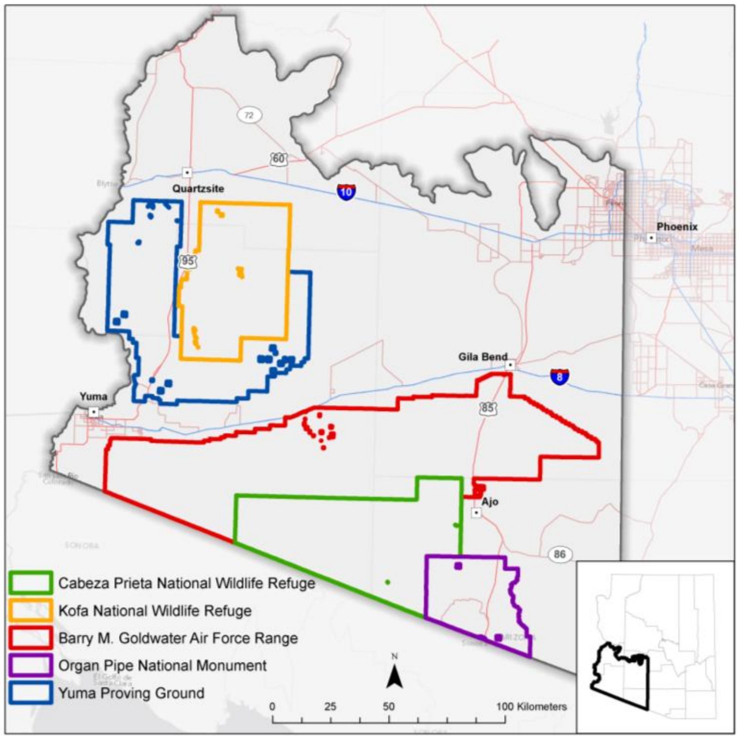

Fig. 3.1 The 45,100-km^2 study area used to model fire likelihood in the lower Sonoran Desert of southwestern Arizona.

Arizona Upland subdivision of the Sonoran Desert that fall within the study area generally support more diverse perennial plant cover (Phillips and Comus 2000). Mean minimum (Dec.) 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 mm and 92 mm, respectively, falls as winter precipitation. The winter of 2004-2005 was particularly wet for this period and region, recording more than 300 percent of the average winter precipitation across the study extent (Western Regional Climate Center 2009, www.wrcc.dri.edu). These wet years, coupled with historical land use (e.g., agricultural) activities, have facilitated increased invasion by non-native invasive plants (Brooks and Pyke 2001). In addition, more than

70,000 ha have burned since 2000, with most (> 75%) of this area burning in 2005. Long fire return intervals are characteristic of the entire study area and fire at any level is a concern to native plant species (Brooks and Chambers 2011).

3.2.3 Fire likelihood in the lower Sonoran Desert

Here we derive a current flow model of fire likelihood for the study area. To map fire likelihood based on high risk fuel conditions, we first used a spatial fire occurrence database from 1989-2010 and mixed-effects logistic regression to estimate the probability (i.e., risk) of a large (≥ 20 ha) fire across the study area (see Chapter 2). We used a Geographic Information System (GIS; ArcGIS v10.1, ESRI, Redlands, CA) to map the modeled predictions across a 450 m (20 ha) gridded landscape of the study area. In this model, we incorporated variables derived from the Normalized Difference Vegetation Index (NDVI) and other landscape variables to estimate annual fire risk. Increased fire activity in the Sonoran Desert depends predominantly on increased production of annual plants (Rogers and Vint 1987). We produced a high fire risk map using maximum NDVI estimates from a year with very high fuel loads (2005). This fire risk map represented one of the parameters used to estimate conductance to fire spread.

Next, we accounted for the interaction between wind direction and topography as an additional conductance parameter. The maximum effect of weather, topography and fuel on fire spread occurs when wind direction is directly aligned with aspect (Whelan 1995). When fuel loads are sufficient to carry fire in the lower Sonoran Desert, fuel moisture does not seem to significantly influence area burned (Crimmins and Comrie 2004). Rather, favorable weather for fire brings dry hot winds that interact with topographic features and will strongly influence burn patterns. We used the program WindNinja (v. 2.1.3; Forthofer et al. 2009) to simulate the effect of terrain on wind flow across the study extent. The program requires an initial domain-averaged wind speed and direction, and outputs the spatial variation based on topography and dominant vegetation. To determine the initial inputs, we generated long-term (1986-2009) monthly averaged wind roses from the Western Regional Climate Center (www.wrcc.dri.edu). For the most active fire months in our study region (April-September), the dominant wind direction was south-southwest and an upper average wind speed was 21 km/hour. We ran simulations for both 180° (south) and 225° (southwest) winds at 21 km/hour. We combined the wind direction outputs and an aspect raster in the GIS to translate the alignment of wind and aspect into a categorized conductance to fire spread (Fig. 3.2). This formed the second parameter used to estimate conductance. The final conductance was an additive combination of fire risk and wind influences.

The current flow model was implemented in the Circuitscape environment, an open source software that uses circuit theory to predict connectivity across large landscapes (McRae and Shah 2011). To get at overall landscape conductance, we used a 'wall-to-wall' approach by running the model with one whole edge of the study extent assigned as the source and the opposite edge as the target (Anderson et al. 2012) . We repeated this method for each of four source-target pairings (north-south, south-north, east-west, west-east) and each of two conductance scenarios (180° and 225° winds), for a total of eight model runs. We summed the results of these model runs, and the combined output was a high risk scenario of fire likelihood. Hereafter, we refer to the 80th percentile of fire likelihood as relatively high fire likelihood (HFL).

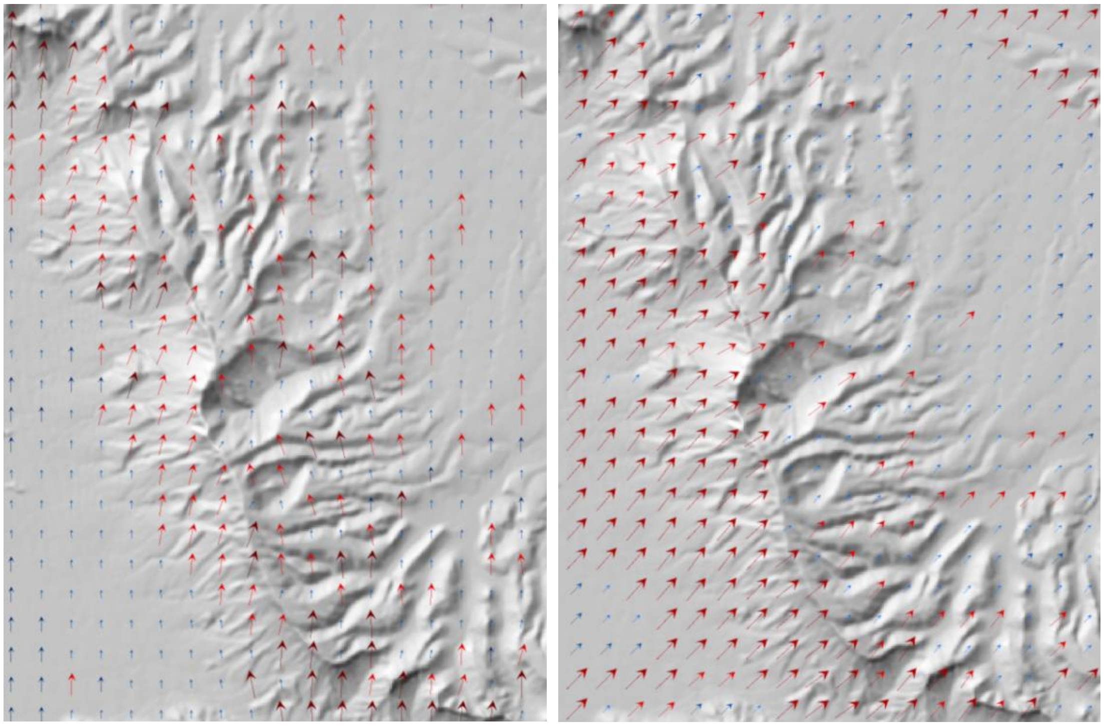

Fig. 3.2 Alignment of wind direction and aspect used as a parameter in estimating the landscape conductance to fire spread. Larger, red arrows represent lower cost to fire spread and smaller, blue arrows represent higher cost to fire spread, for 180 degree winds (left) and 225 degree winds (right).

To assess the accuracy of our high likelihood estimates, we evaluated contiguous areas of HFL against historical fire perimeter data. We used fire perimeters that were delineated as part of the Monitoring Trends in Burn Severity (MTBS) project (www.mtbs.gov), which maps fires that burned greater than 1000 acres since 1984. The measure of association used was the kappa coefficient,

$$\kappa = \frac{P-E}{1-E},$$

where the observed proportion, P, represents the proportion of the historical fire perimeter that was estimated as HFL, and the expected proportion, E, represents a random proportion of association (Morais 2001). The value of kappa ranges between -1, which represents perfect disagreement between predicted HFL and historical burned area, and 1, which represents perfect agreement. Values close to zero indicate that the agreement is no better than would be expected by chance. We used the R statistical environment (v2.15.1; www.r-project.org) to calculate values of *P* and *E* for each fire perimeter. To calculate *E*, we generated 1000 random distributions of the historical fire perimeter data, and calculated the mean value of *E* for each perimeter.

3.2.4 Fire impacts in the lower Sonoran Desert

We demonstrated how HFL can be integrated into a spatial management framework with information on how fire might impact resources that are highly valued by society. We first categorized the degree to which future fire exposure is expected to impact native plant community composition, taking into account major vegetation associations and impact of repeated fire. This approach relied on the notion that higher productivity in functionally diverse native plants increases the capacity of native communities to compete with invasives and recover after fire (Wisdom and Chambers 2009). Thus, repeated fire may differentially impact plant communities based on their capacity for fire resiliency (Brooks and Chambers 2011). Differences in plant productivity were broadly grouped into the two major subdivisions of our study area – the Lower Colorado subdivision and the Arizona Upland subdivision. While these subdivisions were created solely in reference to the vegetation, they parallel other ecological gradients that influence fire resiliency, such as available precipitation and nutrient resources (Shreve and Wiggins 1964, Comrie and Broyles 2002). The Arizona Upland subdivision harbors higher plant productivity and diversity and thus was assumed to display higher fire resiliency. We used the MTBS fire perimeters to determine whether a specific location had burned in an extent greater than 405 ha (1000 ac) between 1984 and 2010. We merged these two datasets in the GIS, and the resultant data layer comprised three relative categories of fire impact – moderate, high and very high. Moderate fire impact was assigned to unburned areas of the Arizona Upland subdivision, high fire impact was assigned to unburned areas of the Lower Colorado subdivision or burned areas of the Arizona Upland subdivision, and very high fire impact was assigned to burned areas of the Lower Colorado subdivision.

We identified three important ecological attributes in our study area that are directly at risk of large fire and whose loss or degradation would negatively affect other ecosystem processes, namely wilderness areas, ephemeral and intermittent streams, and habitats for sensitive species of wildlife, specifically the endangered Sonoran pronghorn (*Antilocapra Americana sonoriensis*) . Designated wilderness provides important, largely undisturbed habitat for wildlife and plant species in the region. We acquired GIS data for all wilderness areas in the study area from a public database (www.wilderness.net). Ephemeral and intermittent streams support rich plant diversity during episodic water pulses (Stromberg et al. 2008). Changes to their associated plant communities would disrupt important microhabitats and wildlife corridors, as well as hydrologic connectivity (Levick et al. 2008). We acquired GIS data for major ephemeral washes from The Nature Conservancy's Arizona Freshwater Assessment (www.azconservation.org). Fire effects on plant community composition and ecosystem processes are also a primary concern to habitat quality for wildlife species with narrow habitat requirements. We acquired a shapefile of the current Sonoran pronghorn range from the BLM (www.blm.gov/az/st/en/prog/planning/son_des/docs/lsf-sdnm-gis.html) and potential Sonoran pronghorn habitat data from the Arizona Game and Fish Department (O'Brien et al. 2005). The current occupied range for the Sonoran pronghorn is approximately 4,595 km^2 within the southern extent of our study area, and 18,870 km^2 of our study area has been identified as additional suitable habitat (O'Brien et al. 2005). We focused our analysis on three case studies within the study area – the Kofa wilderness, the Rainbow Valley, and suitable habitat for the Sonoran pronghorn – to offer examples for managers concerned with fire.

3.3 Results

3.3.1 Fire likelihood

The wind and terrain influences on fire spread showed strong patterns that were congruent with the topography of our study area. Low-lying bajadas that are characteristic of the lower Sonoran Desert are intersected throughout by ridgelines oriented in a predominant southeast-northwest direction. For 225 degree winds, areas most conducive to fire spread were consistently on the immediate windward side of ridgelines, whereas areas least conducive were on the leeward side. Intermediate areas were typically found in the valleys between ridgelines. The influence of 180 degree winds showed similar patterns, but in general, areas on the windward side of ridgelines were less conducive to fire spread.

For the current flow model, the average value of kappa was $\kappa = 0.53$ (n=16), indicating moderate agreement between what actually burned and our estimates of high fire likelihood (Table 3.1; Monserud and Leemans 1992). The map output showed current flow across the study area, representing fire likelihood under high risk conditions (Fig. 3.3). 19% of the study area was estimated as HFL, and of this area, 7% was estimated to have very high fire impact, 85% was estimated to have high impact, and 8%

Table 3.1 Values of the kappa statistic (κ) used to evaluate the level of agreement between historical fire perimeters and estimated High Fire Likelihood (HFL).
Values range from -1 (perfect disagreement) to 1 (perfect agreement).

Fire Name	Fire Size (ha)	kappa (κ)
King Valley	13,836	0.96
Eagle Eye	932	0.83
Bighorn	2,377	0.62
Bobby	2,038	0.64
2000	918	0.56
Unnamed	3,860	-0.07
Camino	463	1.00
Growler Peak	11,000	0.99
Theba	2,350	0.41
Goldwater	26,365	0.48
Sand Tank	4,908	0.43
Tracks	2,282	-0.21
Crater	5,447	0.93
Home	594	-0.22
Getting	572	0.60
Montezuma	2,682	0.49
	Total: 80,624	**Mean: 0.53**

was estimated to have moderate impact. The patterns of high current flow reflected those of high fire risk but were generally more spatially contiguous. Flow tended to be concentrated over larger areas where wind direction would most facilitate the spread of fire. In contrast, flow tended to channel through or avoid areas where wind moves downslope.

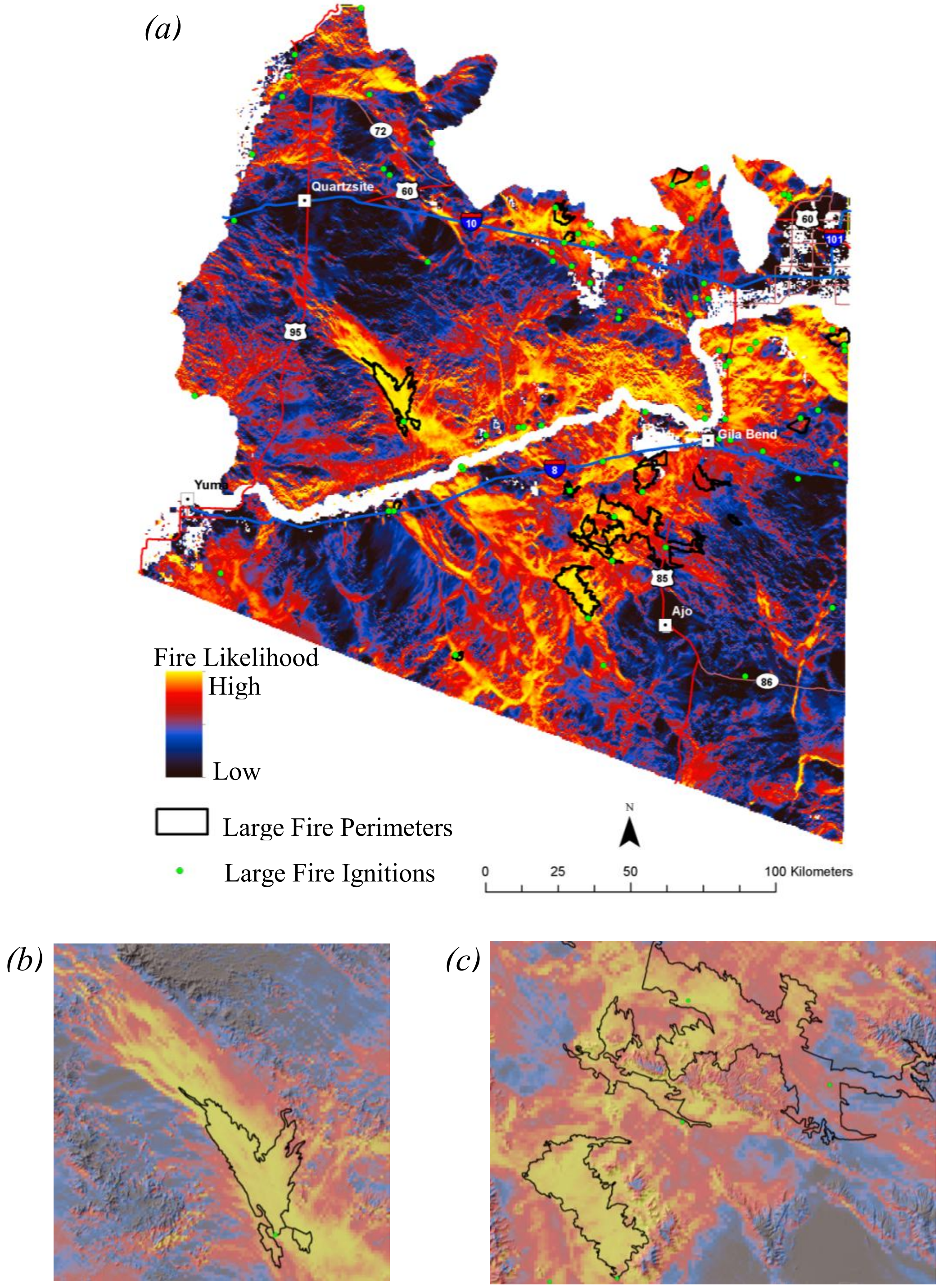

Fig. 3.3 *(a)* Current flow map of fire likelihood across the lower Sonoran Desert of southwestern Arizona. Warmer colors indicate relatively high current density, or higher likelihood of fire, and colder colors indicate relatively low current density, or lower likelihood of fire. *(b)* Detail of the 2005 King Valley Fire. *(c)* Detail of the Growler Peak, Crater, and Goldwater fires, all large fires that burned in 2005.

3.3.2 Fire impact case studies

1. Wilderness

HFL was estimated in 36,530 ha (17.5%) of the Kofa wilderness, with 27%, 69% and 4% of HFL predicted to have very high, high and moderate fire impacts, respectively (Fig. 3.4). The 27% estimated to have very high impact covered one contiguous patch in the Lower Colorado subdivision, which previously burned in the 2005 King Valley fire. The 69% of HFL estimated to have high impact was also within the Lower Colorado subdivision and primarily extended from the King Valley burn perimeter, but has not burned in a large fire since 1984. Smaller patches of moderate impact HFL were estimated in areas of higher topographic relief in the wilderness, where in some areas it connected with patches of high impact HFL in the adjacent lowlands. The prevailing pathway of HFL crossed the boundary with the YPG on the south, and passed through KNWR non-wilderness further north.

2. Ephemeral and Intermittent Streams

Of roughly 90,000 ha that comprise the Rainbow Valley, 48,000 ha (53%) were estimated as HFL and were concentrated on the northeastern side of the main Waterman Wash (Fig. 3.5). Of this, 91% was predicted to have high fire impact and occurred mostly as one spatially contiguous patch in the Lower Colorado subdivision. Nine percent was estimated to have moderate fire impact, and these areas extended from HFL in the valley lowlands to upland headwaters in the Sierra Estrella and Maricopa mountains. Three major pathways of HFL crossed over the Waterman Wash, including one pathway that covered the majority of a critical habitat linkage (Beier et al. 2008). The habitat linkage delineates a total of 12,107 ha across the valley, of which 9,777 ha (81 %) was estimated as HFL.

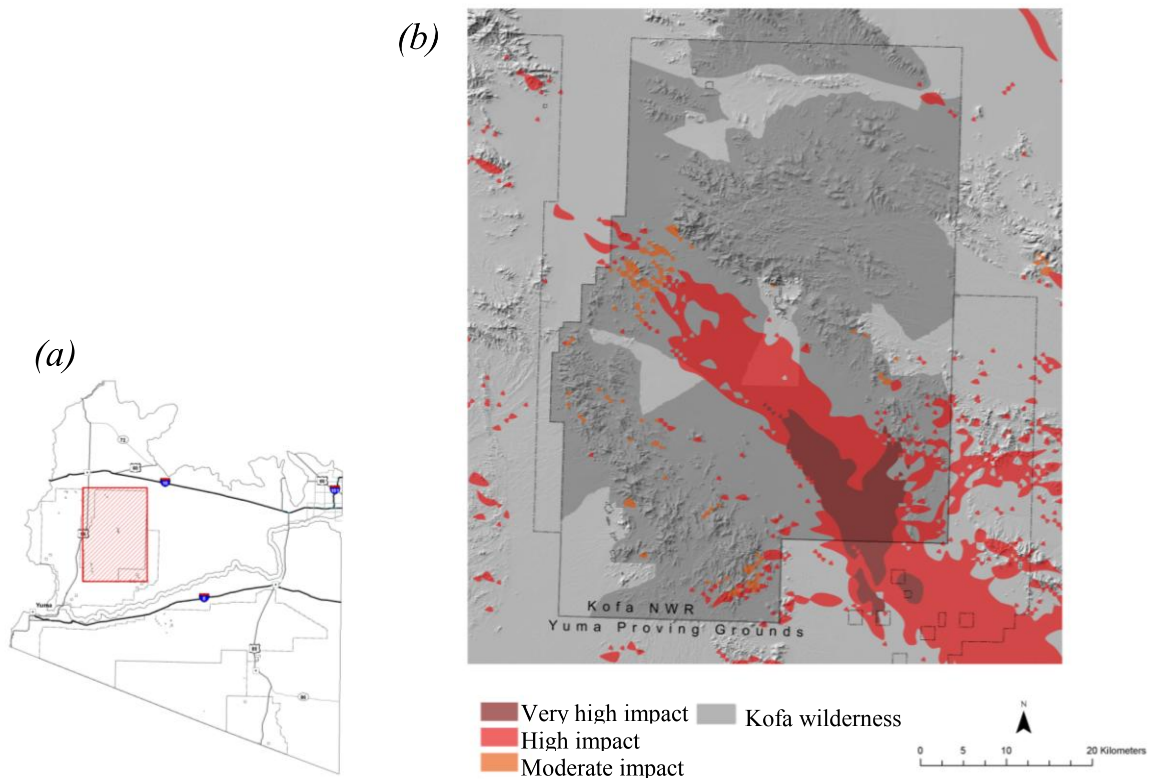

Fig. 3.4 Fire likelihood and fire impacts in the Kofa wilderness. *(a)* Location of the Kofa wilderness within the study area. The wilderness encompasses a total of 208,900 ha within the KNWR and ranges between 205 m and 1,480 m elevation. The entire wilderness is managed by the US Fish and Wildlife Service, and is bordered on the south and east by the YPG and on the north, west and east by Bureau of Land Management (BLM) lands. *(b)* Estimated High Fire Likelihood (HFL) categorized by expected fire impact in the Kofa Wilderness. HFL expected to have very high impact occurs in the burn perimeter of the 2005 King Valley fire, and high impact HFL extends beyond the burn perimeter and within the Lower Colorado subdivision of the Sonoran Desert.

3. Sonoran pronghorn habitat

HFL occurred in 1,165 km^2 (25%) of the currently occupied range of the Sonoran pronghorn (Fig. 3.6). Of this area, 13%, 85%, and 2% of HFL was estimated to have very high, high and moderate fire effects, respectively. HFL occurred in 3,342 km^2 (18%) of the additional suitable habitat that has been identified across the study area. These areas were primarily in lower elevations to the north and south of the Gila River corridor, as well as immediately west of the currently occupied range. Some large contiguous extents of additional suitable habitat that were not delineated as HFL were on La Posa Plain and extending up to the Kofa Mountains, the Castle Dome Plain extending up to the foothills of the Castle Dome Mountains, and the Lechuguilla Desert.

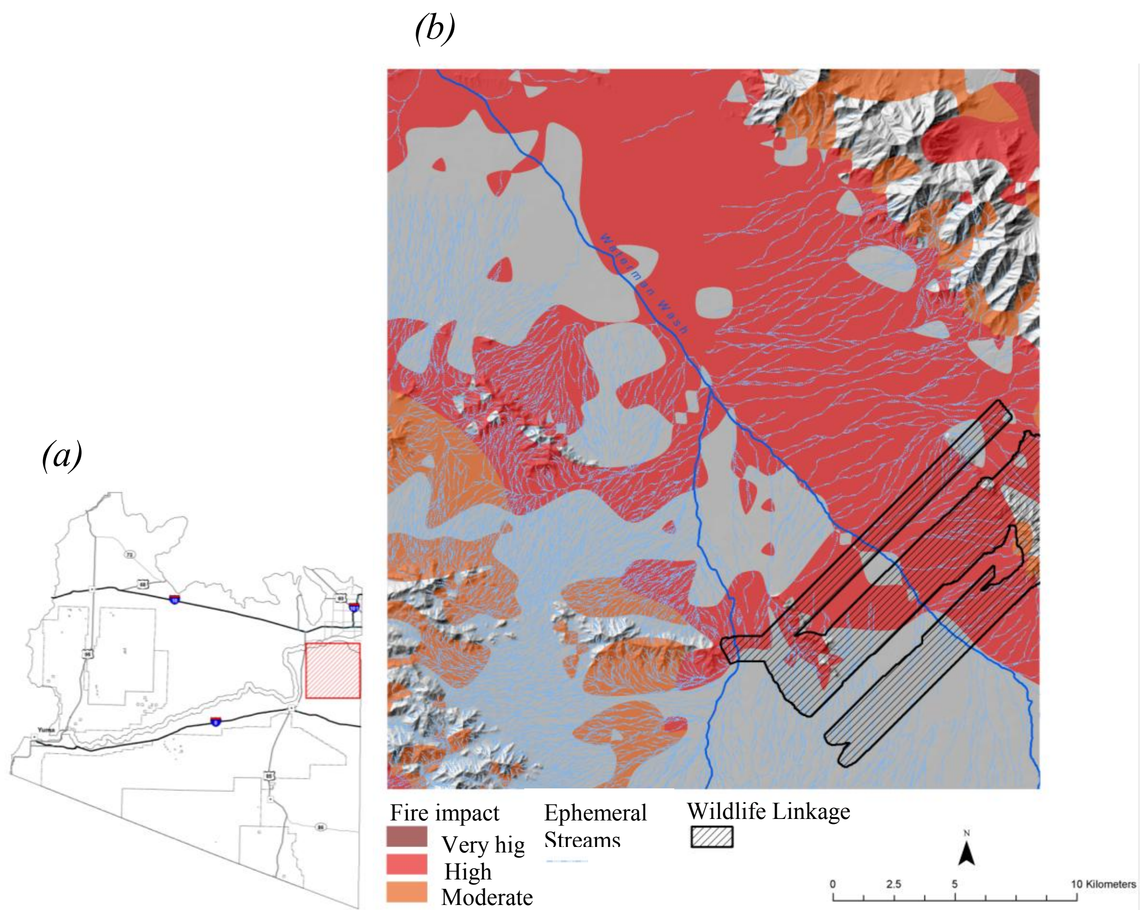

Fig. 3.5 Fire likelihood and fire impacts in the Rainbow Valley. *(a)* Location of the Rainbow Valley within the study area. *(b)* Estimated High Fire Likelihood (HFL) categorized by expected fire impact in the Rainbow Valley. The valley lies between two prominent mountain ranges in the study area, the Sierra Estrellas and the Maricopas, which create numerous small washes converging into the larger Waterman Wash. Portions of the valley have been systematically identified as a critical habitat linkage (Beier et al. 2008). Fire exposure across the valley would be expected to have high impact on the system of ephemeral and intermittent streams that provide corridors for wildlife dispersal.

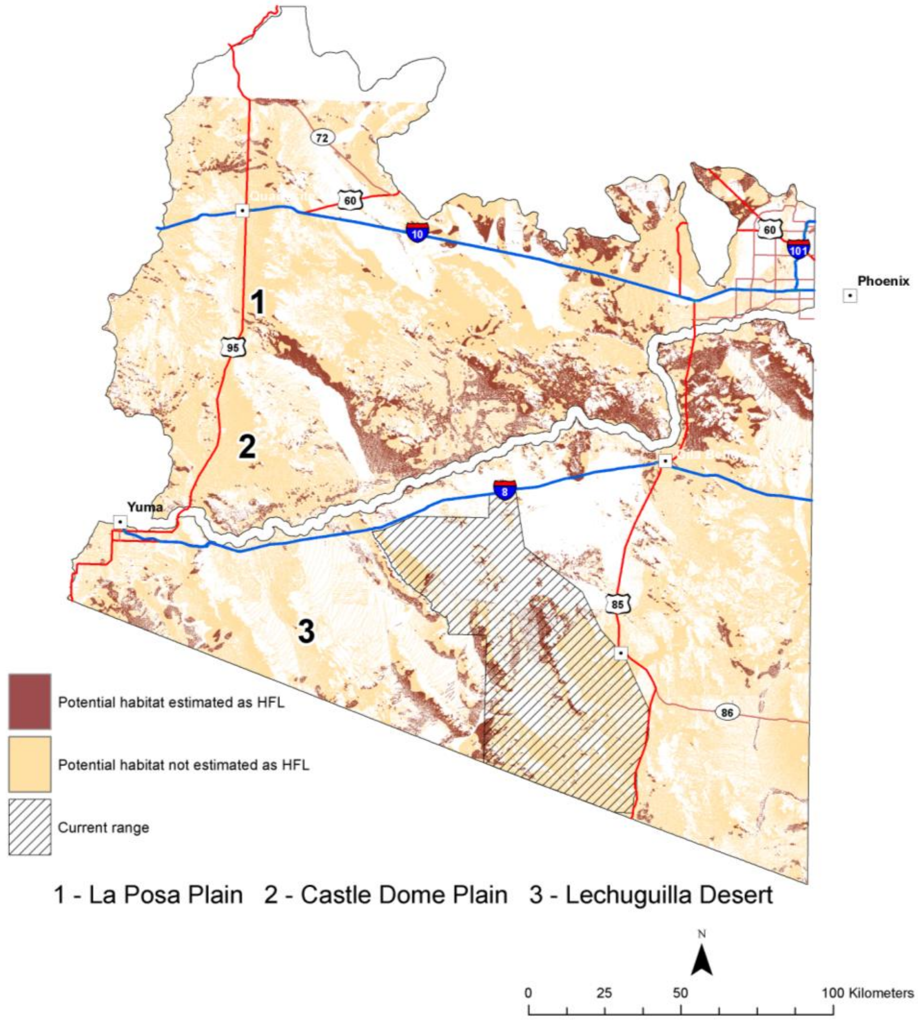

Fig. 3.6 Estimated High Fire Likelihood (HFL) within the current range and potential habitat for the endangered Sonoran pronghorn. Large areas of potential habitat not delineated as HFL may offer potential sites for translocations.

3.4 Discussion

The management of ecosystems will benefit from fire likelihood analyses that account for the local influences on large fire risk, as well as the movement of fire over larger areas. Leveraging models of the local influences on fire occurrence (i.e., using a

GLMM and wind simulations), we have applied a practical and intuitive landscape connectivity model to account for fire spread. Typically, the applications of landscape connectivity encapsulate questions about which patches should be connected to maintain landscape connectedness for an organism. In this context, explorations of fire connectedness may seem less intuitive. Nevertheless, emergent approaches to estimate overall landscape conductance as a function of connectivity capture the essence of landscape-level fire risk analyses (Miller and Ager 2013). Our approach allows large landscapes to be efficiently analyzed, without neglecting the contagious property of fire or assuming where fire starts or stops.

Fire connectivity models embedded in a fire exposure analysis offer unique flexibility and efficiency in meeting management objectives. For instance, landscape-scale estimates of fire likelihood for strategic planning do not need to rely on fire behavior models as they have until now (Thompson and Calkin 2011, Miller and Ager 2013). The use of fire behavior models to simulate an array of fire weather and fuel complex scenarios has the potential to propagate errors, often stemming from a model under-prediction bias (Cruz and Alexander 2010). In the lower Sonoran Desert, distinct differences in inter-annual fuel loads that contribute to fire likelihood are a main concern to fire managers. Estimates of fire likelihood using fire behavior models will rely on custom fuel models, which are likely to be unsuccessful if they are not calibrated against field observations (Cruz and Alexander 2010). Our approach relied on the application of robust fire risk estimates that accounted for annual fuel loads (see chapter 2). Subsequent translation of our connectivity model into a spatial management framework will aid in strategic planning across the lower Sonoran Desert landscape.

3.4.1 Applying fire connectivity models to risk assessment and management

Disruptions to fire regimes that influence the conversion of native desert to non-native invasive grasslands have ecosystem effects that transcend individual jurisdictions (Chambers et al. 2009). Therefore, the need exists for all landowners to work together to strategically address fire management. In the face of global climate and land cover changes, wilderness areas will provide important strongholds for watershed protection, species preservation and habitat conservation, and the role of fire within wilderness should be carefully considered (Miller et al. 2011). Due to the lack of accessibility and high rates of spread, fires that enter wilderness areas are more likely to escape suppression efforts and grow large, when fuel loads are sufficient (see chapter 2). The introduction of human caused ignitions when lightning is absent, as well as the increase of non-native fuels, increases the potential for large fires in wilderness areas (Miller et al. 2011). Our results provide an example of how human caused ignitions proximate to wilderness can be strategically mitigated in order to deter the negative impacts of wilderness fire. Fuels treatments can also be strategically placed to deter fire spread into wilderness. Future fire within the Kofa wilderness, at a high to very high cost to wilderness resources, is most likely to originate from an in-holding of non-wilderness, or from the adjacent YPG. This provides the YPG and KNWR spatially explicit locations of where to coordinate fire management, and specifically where to closely monitor human activities that contribute to increased ignitions.

Our results also demonstrated a case where high fire likelihood threatens a large network of ephemeral washes. Repeat photography from the 13,000 ha King Valley burn site on KNWR provides comparable prospects for long term recovery of xeroriparian networks after fire (Webb et al. 2010). Even without repeated disturbance, it may take hundreds to thousands of years for mature xeroriparian plant communities to reestablish, thus disrupting continuous and diverse chains of vegetation that dispersing wildlife rely on for food and cover (Levick et al. 2008). These dispersal mechanisms in the Rainbow Valley provide important wildlife connectivity between the Sierra Estrella and Maricopa Mountains, where proposed urban developments already threaten connectivity, and would likely increase human-caused ignitions at the wildland urban interface (Beier et al. 2008). The BLM is the major federal landowner within the valley and on either side of the habitat linkage, and therefore has an interest in preventing fires spreading from adjacent state and private lands. A memorandum of understanding between BLM and local jurisdictions, in which the BLM provides wildland firefighting capacity, and local land use plans take fire prevention measures, would be one option to mitigate fire likelihood in the Rainbow Valley.

Our map-based results can aid in the management of critical habitat for sensitive and endangered animal species, including the Sonoran pronghorn. Reproduction and resource use by the Sonoran pronghorn are closely tied to precipitation and access to quality forage, and severe drought conditions in 2001-2002 brought the subspecies population down to only 21 individuals (Hervert et al. 2005). Because the population is isolated in their current habitat, the impact of drought is exacerbated by the fact that they cannot pass barriers to find better forage and water (McCullough et al. 2005). Although the impacts of repeated fire to long term forage quality are not known, Sonoran pronghorn currently rely on a diversity of plant species that provide sources of water when grasses and forbs become desiccated (Hervert et al. 2005). Fire threatens to eliminate this important patch structure of vegetation. Given the vulnerability of the current isolated population, quantitative assessments of HFL and fire impacts, coupled with new models of suitable habitat, could help inform future translocation efforts (O'Brien et al. 2005).

3.4.2 Model uncertainties and limitations

Our fire likelihood model was derived at relatively coarse spatial and temporal scales, and incorporates simplistic assumptions about many fine-scale processes. For example, the propagation of fire from one cell to another is not based on fire behavior, but rather it is based partially on probabilistic estimates of an ignition event becoming a large fire. Therefore, complex fire behavior or very unusual weather events that can play out over a single fire event may not be captured in a connectivity model. For example, by excluding a few of the smaller areas burned that did not show agreement with our estimates, our model actually showed good agreement with historical data. In spite of its inability to capture fine-scale processes or features, a landscape-level connectivity model can identify large areas of fire likelihood that will likely account for most of the area burned on a landscape.

A related source of uncertainty comes from assigning relative conductance values to an inherently heterogeneous process. Conductance to fire spread can potentially take on a range of values at any one location. The methods we have described rely on merging spatial landscape features with wind scenarios to come up with a single landscape conductance value at each grid cell. Specifying how these two parameters interact to influence fire spread, as well as the number of weather scenarios to include, remain rather subjective in our methodology. Indeed, the nearly infinite number of possible interactions between landscape features and weather sequences has been a major challenge to characterizing fire likelihood for large heterogeneous landscapes (Finney 2005). We believe that parameterizations of conductance values for modeling fire connectivity will be an active area of future research.

3.4.3 Next steps for estimating fire connectivity

Recent advances in approaches to estimating landscape connectivity have great potential for improving the realism and application of fire modeling efforts. The concept of betweenness centrality is one such example (Freeman 1979). Centrality can be described as the importance of a node to facilitating the movement of flow across a network. The essence of a betweenness centrality metric is to evaluate the amount of flow in the network that would not occur if a node were not present (Borgatti and Everett 2006). It is measured by determining the number of times a node is traversed when considering paths between all pairwise combinations of nodes. Current flow models, such as ours, can be integrated into betweenness centrality analyses using available computer programs, in order to present a more complete picture of node importance (Carroll et al. 2011).

We also envision integrating an algorithm of minimum fire travel time into a betweenness centrality analysis. Specifically, the Minimum Travel Time (MTT) approach efficiently solves for simulated fire arrival time across a landscape (Finney 2002). Recent advances in likelihood analyses use MTT to simulate thousands of fires on the landscape and estimate burn probabilities for every landscape grid cell (Miller and Ager

2013). In much the same way that computer programs currently integrate least cost path algorithms into centrality analysis, MTT could also be used to estimate node centrality (Carroll et al. 2011). One variant of the betweenness metric sets a limit on the distance between pairwise nodes, so that unrealistically long distances do not contribute to a node's betweenness (Borgatti and Everett 2006). This has been proposed to reduce computational requirements and to more accurately model processes with limited ranges, such as fire spread (Carroll et al. 2011). Considering the complex topology of fuel patterns, weather sequences, and fire spread, 'bounded distance' betweenness centrality based on MTT could provide similar but more robust information than burn probabilities. Since it is based on fire behavior simulations, this connectivity method would more easily integrate fireline intensity to determine fire effects, and the effect of spotting, accounting for accelerated growth from multiple locations (Finney et al. 2011).

As ongoing changes in climate and land cover are poised to alter the fire regime across a broad scale, land management in the lower Sonoran Desert must address likelihood of the high consequence of fire. Conservation planning at both the local and regional scale can be done with respect to efficient, connectivity-based estimates of fire likelihood and impacts. We have presented a novel approach to modeling fire likelihood that we believe will have applications in other fire-prone ecosystems and will be flexible in meeting management objectives across broad scales and multiple jurisdictions.

4.0 Conclusions

As in other desert ecosystems, fire management objectives in the lower Sonoran Desert need to focus on maintaining or increasing fire resilience, prior to the establishment of an invasive plant/fire cycle (Brooks and Chambers 2011). The issue of fire has only recently begun to enter land management plans in the region, including plans for the YPG and BLM (Bureau of Land Management 2012, US Army Garrison Yuma Proving Ground 2012). Contemporaneous integration of the most appropriate fire risk science and technology would contribute to more effective policy from the offset (Daniels and Walker 2001). This thesis has demonstrated how models and maps of large fire risk and fire likelihood can help to promote ecological fire resilience. However, it’s equally important to consider the resiliency of management policy in the region, or the institutional capacity to respond to and prevent negative fire consequences. Resilience would be maintained when effective fire management is integrated and prioritized within broader ecosystem management goals.

As demonstrated by the first chapter, the use of an NDVI metric in an early warning system for managers would be an appropriate first step to integrate technology into fire management. NDVI metrics can be derived from high spatial and temporal resolution imagery and made available through GIS servers across the region. This provides a low cost, implementable action to serve as a first step in raising fire risk consciousness.

The contributing factors to an invasive plant/fire cycle are all present in the lower Sonoran Desert, including established non-native invasives, large wildfire potential, and land use and climate changes that enhance invasion potential (Esque and Schwalbe

2002). Therefore, cues from other desert ecosystems and recent large fire events are sufficient evidence to continue to raise the issue of fire as a problem. Investing in and building on incremental changes, such as the integration of NDVI into risk forecasting, would begin to make room for resilient fire management. Eventually, longer term strategic planning that integrates estimates of fire likelihood, might have an important niche in ecosystem management policy. Incremental integration of fire risk science and technology could cumulatively build the fire resiliency of the lower Sonoran Desert.

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