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A new model of landscape-scale fire connectivity applied to resource and fire management in the Sonoran Desert, USA

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Abstract. Understanding where and when on the landscape fire is likely to burn (fire likelihood) and the predicted responses of valued resources (fire effects) will lead to more effective management of wildfire risk in multiple ecosystem types. Fire is a contagious and highly unpredictable process, and an analysis of fire connectivity that incorporates stochasticity may help predict fire likelihood across large extents. We developed a model of fire connectivity based on electrical circuit theory, which is a probabilistic approach to modeling ecological flows. We first parameterized our model to reflect the synergistic influences of fuels, landscape properties, and winds on fire spread in the lower Sonoran Desert of southwestern Arizona, and then defined this landscape as an interconnected network through which to model flow (i.e., fire spread). We interpreted the mapped outputs as fire likelihood and used historical burned area data to evaluate our results. Expected fire effects were characterized based on the degree to which future fire exposure might negatively impact native plant community recovery, taking into account the impact of repeated fire and major vegetation associations. We explored fire effects within habitat for the endangered Sonoran pronghorn antelope and designated wilderness. Model results indicated that fire likelihood was higher in lower elevations, and in areas with lower slopes and topographic roughness. Fire likelihood and effects were predicted to be high in 21% of the currently occupied range of the Sonoran pronghorn and 15% of the additional habitat considered suitable. Across 16 designated wilderness areas, highest predicted fire likelihood and effects fell within low elevation wilderness areas that overlapped large fire perimeters that occurred in 2005. As ongoing changes in climate and land cover are poised to alter the fire regime across extensive and ecologically important areas in the lower Sonoran Desert, an analysis of fire likelihood and effects can contribute new and important information to fire and fuels management. Our novel approach to modeling fire connectivity addresses challenges in quantifying and communicating wildfire risk and is applicable to other ecosystems and management issues globally.

Key words: circuit theory; fire connectivity; fire effects; fire likelihood; fire risk management; Sonoran Desert; Sonoran pronghorn; wilderness fire management.

Introduction

Rapid changes to fire regimes are occurring globally, unfolding in many regions with anomalously large or frequent wildfires that can destabilize whole ecosystems (Pausas and Keeley 2009). Strategic planning for high consequence fires requires an a priori understanding of where and when on the landscape fire is likely to burn (fire likelihood) and the predicted response of valued resources (fire effects; Fairbrother and Turnley 2005). Indeed, estimating fire likelihood and effects at meaningful spatial scales may be the most challenging part of fully communicating fire risk for management (Ager et al. 2012). In this paper, we present a circuit-theoretic model of fire connectivity as a novel approach to estimate fire likelihood, which we couple with a fire effects analysis in support of strategic fire and resource planning across a large heterogeneous region of the lower Sonoran Desert in Southwestern Arizona.

Numerous models and tools have been applied to landscape-scale analyses of fire likelihood, although most were designed to replicate the perimeter spread of individual fires (e.g., Parisien et al. 2012, Thompson et al. 2013). For example, simulation models based on the physical and empirical properties of spread, such as FARSITE (Finney 2004) and Prometheus (Canadian Wildland Fire Growth Model Steering Committee 2004), predict the deterministic spread of fire as it is influenced by variable weather, fuel, and topography. The large-fire simulation system (FSim; Finney et al. 2011) uses a computationally efficient formulation of FARSITE to generate Monte Carlo simulations of fire spread and derive the probability of burning for any one

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location. Similarly, BURN-P3 (Parisien et al. 2005) uses the Prometheus fire spread model to simulate a very large number of fires in multiple hypothetical fire seasons to determine overall fire likelihood. The reliability of these Monte Carlo-based simulation methods depends on representing the natural variability in fire ignition and spread by simulating discrete fires with deterministic outcomes. These methods require substantial data collection and calibration efforts to capture the range of variability, including fuel models that feed into fire spread simulations, knowledge of where fire is more likely to start, and historical records of observed fire progression and weather (e.g., Parisien et al. 2012). Where such data is available, results of studies utilizing these methods have agreed well with observed fire occurrence (e.g., Paz et al. 2011) and contributed to significant advancements in landscape-scale fire risk analyses (Miller and Ager 2013).

Our alternative approach to modeling fire likelihood incorporates the spatiotemporal variability in fire spread without relying on the replication of discrete fire events. To begin, the whole landscape is represented as a network, which is a collection of nodes and edges interacting as a system (Proulx et al. 2005). The BurnPro model (Davis and Miller 2004) also uses a network-based approach to analyze the accumulated time of fire spread through a landscape network, where accumulated time is based on the rate of forward spread of a simulated fire. This model estimates fire likelihood based on the length of time between an ignition occurrence and a weather-stopping event and assumes still that fire moves in a deterministic manner by spreading from a source to a target in the least amount of time. Similarly, our network-based approach provides a means to explore the role of spatial context (i.e., the landscape network topology) in influencing the fire contagion process, which is extremely important in predicting fire likelihood (Miller and Ager 2013). However, our approach accommodates important stochastic properties of fire by considering only nearest neighbor effects in the network topology, i.e., a user-defined, adjacent neighborhood is the only influence on fire spread probabilities. Moreover, the approach offers a useful new perspective for investigating fire likelihood across broad spatial and temporal scales and when the objective is not to simulate discrete fire spread at narrow time intervals.

Mathematical approaches to analyzing the behavior of networks, such as graph theory and electronic circuit theory, have been widely used elsewhere in ecology to estimate landscape connectivity for animal populations (e.g., Urban and Keitt 2001, McRae et al. 2008). Landscape connectivity has been defined as "the degree to which the landscape facilitates or impedes movement [of a process] among resource patches" (Taylor et al. 1993). To estimate fire likelihood, we shift the emphasis to overall landscape conductance, i.e., the ability of the whole landscape to facilitate the spread of fire, without regard to a patch-based network. In contrast to models that simulate fire perimeter spread based on physical and empirical properties (e.g., FARSITE and Prometheus), existing mathematically analogous fire models leverage the similarities between fire behavior and mathematical concepts, such as percolation theory and cellular automata (Sullivan 2009). Circuit theory also provides a rigorous mathematical framework that has greatly improved understanding of how environmental factors influence the movement of ecological processes across large landscapes (McRae and Beier 2007, McRae et al. 2008). Ecological connectivity models based on circuit theory are concerned with the stochastic movement of an entity (e.g., a dispersing animal) across an underlying circuit network (McRae et al. 2008). The spread of fire through a circuit network is analogous to the movement of random walkers with no knowledge of the landscape beyond their nearest neighbors. In this case, fire spreads probabilistically to any of the adjacent neighbors in the network. The resultant predictions provide a likelihood-based interpretation of fire-environment interactions, which take into account all possible pathways of fire spread. The specific spatial and temporal environment of most interest for fire and fuels management is defined in the flexible parameterization of the circuit network. Circuit-theoretic models can be run efficiently on very large landscapes (e.g., >1 million cells) and are robust to the spatial resolution of analysis (McRae et al. 2008), which also make them useful for fire likelihood analyses at scales that are meaningful to fire and fuels management planners.

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, but have increased in recent decades (Brooks and Pyke 2001). Introduced annual grasses are a primary driver of increased fire activity in desert shrublands, reinforcing the conversion of native habitats to annual grasslands (Brooks and Matchett 2006, Balch et al. 2013). Together with climatic changes, these introduced grasses also contribute to increasingly dynamic and distinct differences in interannual fuel loads (Abatzoglou and Kolden 2011), which are difficult to represent in current methods to model fire likelihood. Many extant fire spread models such as FARSITE rely on fuel models to generalize the fuel complex and model the combustion process (e.g., Scott and Burgan 2005). The Fuel Characteristic Classification System was designed to facilitate the creation of customized fuel models (Ottmar et al. 2007) because these models can be inaccurate if they are not generated on a regular basis or calibrated against field observations of fire behavior (Cruz and Alexander 2010). Parameterization of circuit-theoretic models is flexible enough that fuels can be represented in a way that is most appropriate to the focal ecosystem and management objective. In the hottest and driest desert shrubland of North America, the lower Sonoran Desert, heterogeneous annual fuel loads are amongst the most limiting factors for large fire occurrence, and need to be well represented in a model of fire likelihood (Gray et al. 2014). Other factors known to influence large fires, such as fuel bed composition and fuel moisture, are less important for fire spread than the amount of accumulated fine fuels that fill the interspaces of otherwise sparse vegetation (Brooks and Pyke 2001).

When large fires do occur in the lower Sonoran Desert, they can have cascading effects on the ecosystem, including loss of habitat for vulnerable wildlife species (e.g., Esque et al. 2013). The long-term fire effects in deserts are related to the capacity of plant communities to recover following fire, known as fire resiliency (Brooks and Chambers 2011). Accordingly, models of fire likelihood across ecological resource gradients can be used to predict fire effects in the lower Sonoran Desert to inform management. Existing management strategies for the endangered Sonoran pronghorn antelope (*Antilocapra americana sonoriensis*), in particular, would benefit from fire likelihood and effects analyses across the current and potential range of the species. In the United States, the current range of the species is restricted to an approximately 7300-km^2 area in southwestern Arizona, and in 2013 a nearby experimental population was reintroduced into its historic range (A. Alvidres, *personal communication*). Given recent patterns of habitat loss, the most effective recovery effort may be to expand populations into their historic range (Wilson et al. 2010). Since increasing fire frequency and size may further impact or eliminate important habitat attributes, a fire likelihood and effects analysis in areas predicted to be suitable for Sonoran pronghorn can help to guide ongoing and future translocation efforts in the lower Sonoran Desert (O'Brien et al. 2005). Similarly, it's desirable for managers to understand fire likelihood and effects across protected areas in this region so that ad hoc management does not compromise the natural or social value of these places. The unique ecosystem characteristics of the Sonoran Desert, including low human population densities and intactness of natural habitat, hold global significance for biodiversity conservation (Mittermeier et al. 2003). Nearly 12 000 km^2 of southwestern Arizona is protected as federal wilderness and managed specifically to preserve the natural and wild characteristics of the Sonoran Desert.

Within this context, the principal objectives of our research were to model and map fire likelihood and effects across much of the lower Sonoran Desert in southwestern Arizona, and to demonstrate the application of these outputs in a spatially explicit management framework. Specifically, we sought to (1) parameterize the landscape conductance for fire spread in this region; (2) use the resulting conductance surface to produce a fire connectivity model and translate outputs to maps of fire likelihood; and (3) produce a map of expected fire effects based on existing knowledge of fire resiliency in the lower Sonoran Desert. Our primary goal was to demonstrate how circuit-theoretic and model-based estimates of fire likelihood can be coupled with expected fire effects to inform regional habitat and wilderness management in the Sonoran Desert. Our approach to modeling fire connectivity is highly transferable to other ecosystems where fire dynamics are manifest over broad spatial and temporal extents and across multiple jurisdictions.

Methods

Modeling fire connectivity

The underlying networks in circuit-theoretic models are analogous to electrical circuits and are defined by a graph structure of interconnected nodes and conductors (McRae 2006). The application of circuit-theoretic models is rooted in the connection between electrical networks and random walks, where equations describing current flow through an electrical circuit can be used to estimate the expected movement of random walkers on a corresponding circuit network (e.g., McRae 2006). In this network, a random walker moves from node x to adjacent node y with probability given by

$$P_{xy} = \frac{C_{xy}}{C_x}$$

where C_{xy} is the conductance from x to y and $C_x = \sum_y C_{xy}$ (Doyle and Snell 1984). Whole contiguous landscapes can be modeled as circuit networks by representing landscape grid cells as nodes connected to adjacent nodes by conductors, which we refer to as a conductance surface (the inverse of a resistance surface; McRae et al. 2008). An ecological flow is represented by a current input that originates from a source and moves through the network until it reaches a target. Circuit and random walk theory show that the resulting current density i_{xy} between any two adjacent nodes is equal to the net, directionless likelihood of flow passing between those nodes, such that

$$i_{xy} = |u_x P_{xy} - u_y P_{yx}|$$

where u_x and u_y are the expected number of times flow passes through x and y, respectively (Doyle and Snell 1984). Put more simply, the current passing between a pair of nodes is the expected net number of times a flow would move between them on its way from source to target, where 'net' means that flow one way and back again is erased. In the following paragraph, we describe how these general methods of circuit theory and landscape connectivity can be applied to fire spread and estimates of fire likelihood.

Landscape conductance in a circuit-theoretic model is a surrogate for the ease of movement through the modeled environment (McRae et al. 2008), and we begin by parameterizing the conductance surface for fire spread. Logistic regression models are commonly used to derive continuous maps of the conditional probability that an ignition occurrence will become a large fire (e.g.,

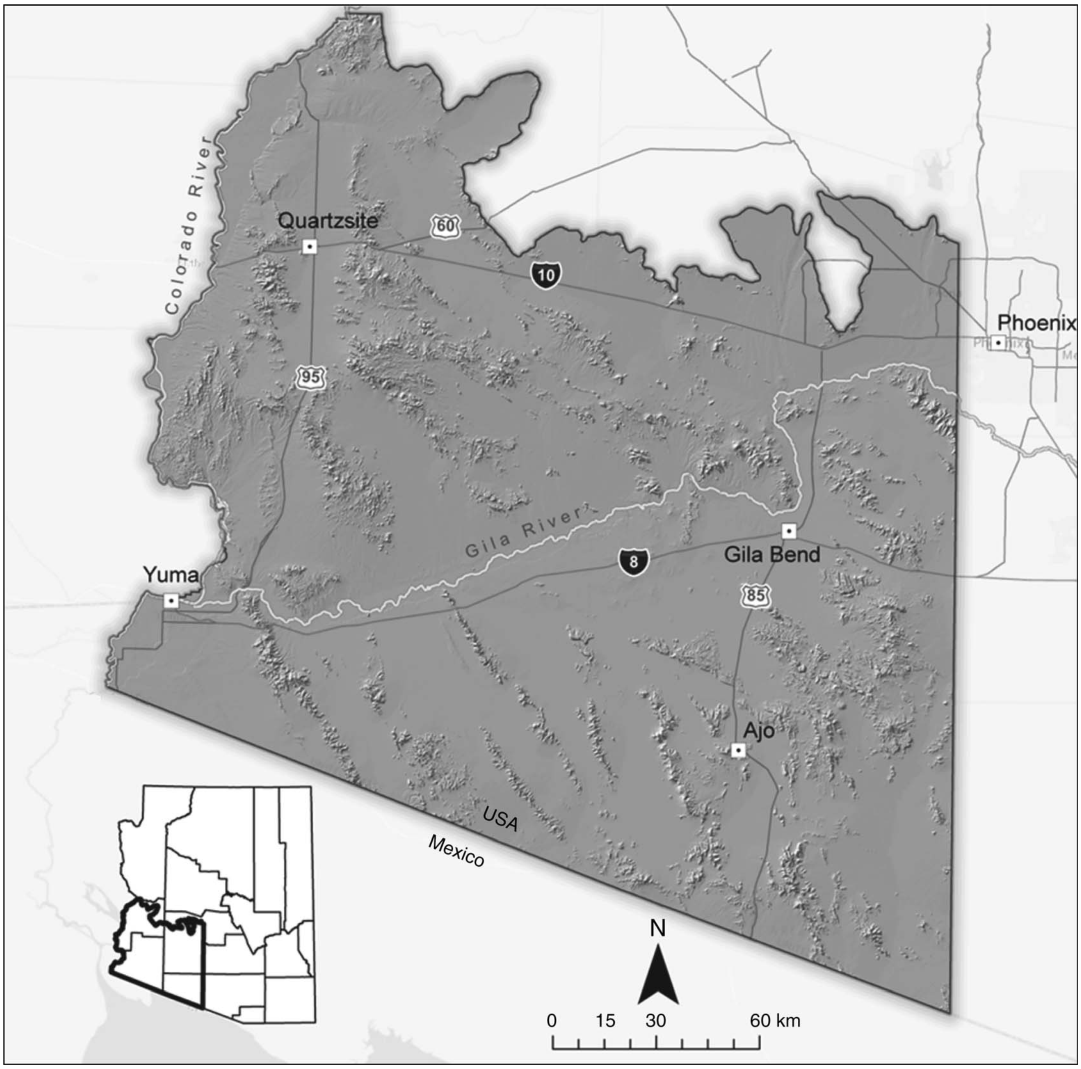

FIG. 1. The 45 100-km^2 study area used to estimate fire likelihood and fire effects in the lower Sonoran Desert of southwestern Arizona, USA. This subdivision of the Sonoran Desert is extremely hot and dry and is not well adapted to fire. However, it is likely that future climate change and invasions by nonnative plants will contribute to increased fire occurrence.

Preisler et al. 2011, Hawbaker et al. 2013, Gray et al. 2014). The probabilities reflect an isolated likelihood that an ignition will result in a fire of at least some observed size, and do not account for fire spread dynamics beyond that specific location and size threshold. In contrast to simulation tools that account for contagion, such as FARSITE and Prometheus, these statistically derived outputs are limited in their capacity to predict fire likelihood (Thompson and Calkin 2011). In a circuit-network representation of these models, the statistically derived probabilities would presumably have a large influence on the strength of conductors, reflecting the probability of individual ignitions becoming large and spreading to adjacent nodes. Therefore, our fire connectivity model treats the conditional probability of large fire as one parameter in defining landscape conductance. Terrain-influenced wind speeds and directions are also incorporated as additional parameters in defining conductance. Thus, large fire probability and wind vector maps are the principal data that comprise a conductance surface. Since the relative influences of spatial controls on fire vary between landscapes (e.g., Rollins et al. 2002), parameterizing the conductance necessarily requires a local- to landscape-scale approach. When fire spreads through the circuit network, resulting estimates of current density are equivalent to the net passage probabilities of modeled fire spread (i.e., fire likelihood) that account for landscape-specific spread dynamics.

Study area

Our 45 100-km^2 study area is located in the lower Sonoran Desert of southwestern Arizona, USA (Fig. 1). The mean elevation of the study area is 372 m, and ranges from <100 m to nearly 1500 m. Numerous small mountain ranges are separated by expansive desert valleys, plains, and bajadas that typify the Lower Colorado River subdivision of the Sonoran Desert (Brown 1994). Portions of the 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 (December) and maximum (July) temperatures range approximately between 6°C and 40°C. Long-term (1952–2012) average annual precipitation was 95 mm at lower elevations and 162 mm at higher elevations, and approximately 60% fell in the winter (December–February; data from National Climatic Data Center, *available online*).[4] The winter of 2004–2005 recorded more than 300% of the average winter precipitation across the study extent (PRISM Climate Group, data *available online*).[5] In 2005, 519 km^2 of the study area burned, representing 89% of the total area burned between 1989–2010. Long fire return intervals are characteristic of the study area, and recurrent fire even at low intensities can significantly reduce native cover and create niches for nonnative invasive plants (Brown and Minnich 1986). Within the study area, our modeling excluded the Gila and Colorado River corridors, agricultural lands, and developed areas, since we were only interested in fire likelihood in desert scrub vegetation.

Estimating fire likelihood

Conditions for large fire occurrence are rare in our study area and we were primarily concerned with a worst-case scenario of fire likelihood, which we represented with conditions of high fire hazard (Hardy 2005). To model fire likelihood under high fire hazard, we first used a spatial database of fire occurrence spanning 22 years, multiple phenometric and other landscape variables, and mixed-effects logistic regression to estimate the conditional probability of a large (≥20 ha) fire (Gray et al. 2014). We chose 20 ha as the large fire size threshold because fires of this size are a good indication that the annual fuel load is sufficient for further fire spread (W. Reaves, *personal communication*). Increased fire activity in the lower Sonoran Desert that depends predominantly on increased production of annual plants is strongly influenced by heterogeneous precipitation patterns (Crimmins and Comrie 2004). The final conditional probability model, which provided strong evidence to historical data, derived estimates of fuel-load variables that are robust to heterogeneous antecedent precipitation occurring over a 22-year time period. The maximum annual Normalized Difference Vegetation Index (NDVI) of the fire year, and the year prior to fire occurrence, can be used as proxies of the total available fuel load (Gray et al. 2014). Both of these variables were considered strong drivers of large fire probability, along with elevation, road density, vegetation heterogeneity, and slope aspect. In our study area, annual fuel loads sprung up in the winter of 2004 and proliferated into 2005, contributing to a year of relatively high fire probability in the 22 years that we examined. From the logistic regression model, we derived a map using estimates of the maximum NDVI from 2004 and 2005, to represent annual large fire probability under conditions of high fire hazard. We used a geographic information system (GIS; ArcGIS v10.1, Esri, Redlands, California, USA) to generate model inputs and map predictions at a 450-m resolution, such that each grid cell was 20 ha. This grain size corresponded with the large fire threshold, and was thus a minimum, sufficient grain size to introduce into a conductance surface.

Next, we considered the interaction between wind and topography as an important control on fire spread. The maximum effect of wind and topography 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 fire weather brings dry hot winds that interact with topographic features and strongly influence burn patterns. We used the program WindNinja (v2.1.3, Missoula Fire Sciences Laboratory, Missoula, Montana, USA) 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 computes the spatial variation in these parameters based on topography and dominant vegetation. To determine the initial inputs, we generated long-term (1986–2009) monthly averaged wind roses from Meso West (data *available online*).[6] For the most active fire months in our study region (May–July) and daily burning period, the dominant winds were south-southwest with observed 10-minute average speeds of 12.9–20.9 km/h. Since peak winds within 10-minute averages significantly affect fire growth, we used a probable maximum 1-minute speed of 30 km/h (Crosby and Chandler 2004). Thus, we ran simulations for both 180° (south) and 225° (southwest) wind directions and wind speeds of 30 km/h. Following the fire modeling standard (Scott 2012), we categorized the terrain-influenced winds by their direction relative to the upslope direction (1, downslope winds; 2, quarter-downslope winds; 3, cross slope winds; 4, quarter-upslope winds; 5, upslope winds). In addition, we categorized the terrain-influenced winds by their speed relative to the initial input of 30 km/h (1, wind speeds ≤30 km/hour; 2, wind speeds >30 km/h). Using the GIS, we derived a 450-m resolution grid based on an

[4] http://www.ncdc.noaa.gov/cdo-web/datasets/ANNUAL/stations/COOP:024702/detail

[5] http://prism.nacse.org/recent/

[6] http://mesowest.utah.edu/cgi-bin/droman/mesomap.cgi?state=AZ&rawsflag=3

equal-weighted overlay of the wind speeds and directions.

The cumulative conductance values used to estimate fire likelihood were an additive combination of conditional large fire probability (scaled from 0 to 1) and spatially varying winds (rescaled from 0 to 1). We assumed a greater influence of fuels on fire spread and therefore assigned half the weight to winds as to large fire probability. The summed values comprised a conductance surface that was represented as a circuit network in the fire connectivity model, to reflect the probability of fire spread between adjacent "ignited" nodes. To estimate fire connectivity, we used Circuitscape (v3.5.8), an open source software program that applies circuit theory to predict current flow across large landscapes (McRae and Shah 2011). We used a "wall-to-wall" approach (Anderson et al. 2012, Pelletier et al. 2014) to account for overall landscape conductance by implementing two model runs: one that forced current vertically north-south and south-north, and one that forced current horizontally east-west and west-east. This was done by assigning one horizontal or vertical edge of the study extent as a single source region and the opposite, parallel edge as a target region, where each edge was one grid cell in width (i.e., 450 m). We repeated this method for two conductance scenarios (180° and 225° winds), for a total of four model runs. The map outputs resulted in a current density for every grid cell, which is equivalent to the net, directionless likelihood of fire spreading through that cell. Within the GIS, we summed these grid-based model outputs together and used the result to represent the cumulative fire likelihood. This approach differs from other methods to estimate fire likelihood that are based on distributed fires across a landscape with individual starting and stopping events (e.g., Finney et al. 2011, Ager et al. 2012). These events are typically drawn from probability distributions of burn duration and fire-season weather, so that the results represent long-term, annualized burn probabilities. Without sufficient data to model such events, our approach was meant to avoid these assumptions and to fully represent all possibilities of fire spread in a year with high fire hazard (i.e., 2005). Additionally, Ager et al. (2012) were only concerned with larger fires and conditioned their estimates of burn probability on fire events that exceeded 1000 ha. Our results are also conditional on large fire occurrence (i.e., 20 ha), but this definition of large fire can be considered unique to our study area.

To examine the predictive performance of the fire connectivity model, and compare it to readily available FSim burn probability estimates in our study area, we used a method that relies on burned area data and makes no assumptions about areas that have not burned. Boyce et al. (2002) presented a similar approach with presence-only validation data to assess the ability of resource selection functions to consistently predict habitat use within levels of suitability. We used 13 years (2000–2012) of moderate resolution imaging spectroradiometer (MODIS) satellite-based burned area data (500-m pixel resolution) to identify grid cells used in the evaluation (data *available online*).[7] We distributed all fire likelihood cells into 10 quantiles and calculated the proportion of evaluation cells observed to occur within each quantile "bin." We repeated this for FSim burn probability estimates derived by the Fire Program Analysis System and clipped to our study area (data *available online*).[8] We also calculated the proportion of all fire likelihood (or in the case of FSim, burn probability) cells to occur within each bin and considered this the proportion expected by chance. The ratio of observed to expected proportions within each bin indicates a frequency of fire presence relative to chance, and lower ranked bins should have a ratio less than one, whereas higher ranked bins should have a ratio increasingly greater than one (Hirzel et al. 2006). To evaluate model performance, we also plotted this ratio against the ranked bins and calculated a Spearman rank correlation coefficient (r_S). High positive values of r_S would result from an increasing curve and would indicate that the ratio increases as fire likelihood or burn probability increases. We considered values of $r_S >$ 0.80 as indicative of exceptional support. In addition to assessing the predictive performance of the cumulative connectivity model, we compared the predictive performance of each model run individually. This allowed us to examine the sensitivity of the final connectivity model to individual scenarios of wind direction and source-target pairing.

Evaluating fire effects

Taking into account the impact of repeated fire and major vegetation associations in the lower Sonoran Desert, we characterized fire effects based on the degree to which future fire exposure is expected to negatively impact native plant community recovery. This approach relied on the notion that higher productivity and diversity of native plants increases fire resiliency (Wisdom and Chambers 2009), and that repeated fire will differentially impact plant communities based on their fire resiliency (Brooks and Chambers 2011). Differences in plant productivity and diversity were broadly grouped into the two ecological subdivisions of our study area: the Lower Colorado River 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 (Shreve and Wiggins 1964, Comrie and Broyles 2002). The Arizona Upland subdivision harbors higher plant productivity and richness and thus was assumed to display higher fire resiliency. We retrieved a shapefile of these subdivisions, which was digitized from the original

[7] http://modis-fire.umd.edu/BA_getdata.html

[8] http://www.forestsandrangelands.gov/WFIT/applications/FPA/index.shtml

1980 map *Biotic Communities of the Southwest* (Brown and Lowe 1980; shapefile *available online*).[9] We also used mapped fire perimeters from the Monitoring Trends in Burn Severity project, which provides a consistent and continuous source of mapped fire perimeters >405 ha, from 1984 to 2011 (data *available online*).[10] We used these data to determine whether a specific location had burned within the perimeter of a large fire in the recent past. We merged these two data sets in the GIS and assigned the outputs to relative classes of fire effects based on the association with expected fire resiliency. We assumed that fire would have the least negative effect in unburned extents of the Arizona Upland subdivision, with more negative effects in unburned extents of the Lower Colorado River subdivision or burned extents of the Arizona Upland subdivision, and the most negative effects in burned extents of the Lower Colorado River subdivision. Since the lower Sonoran Desert is not well adapted to fire and large fire anywhere is expected to have at least moderately negative effects, we assigned these outputs to moderate, high, and very high fire effect classes, respectively.

Next, we focused on understanding the potential negative effects of large fire on two assets of ecological and conservation significance in the study area, namely, habitat for endangered Sonoran pronghorn antelope and federally designated wilderness areas. We acquired a shapefile of the current Sonoran pronghorn range from the U.S. Department of Defense and potential Sonoran pronghorn habitat data from the Arizona Game and Fish Department (O'Brien et al. 2005). We acquired GIS data for all wilderness areas in the study area from a national public database (*available online*).[11] Hereafter, we refer to areas within the 80th percentile of our fire likelihood estimates as areas of relatively high fire likelihood (HFL). For pronghorn current range and potential habitat and for each wilderness area, we calculated the area of HFL by fire effects class.

Results

Fire likelihood

Our historical fire evaluation data set consisted of 4003 burned pixels comprising approximately 2% of the study area. Our mapped predictions offered exceptional empirical support ($r_S = 1.00$) when evaluated with the MODIS burned area data (Figs. 2 and 3). In addition, the cumulative model smoothed over variation among the four individual model runs. For the vertical implementation of the model (225° winds, $r_S = 0.99$ and 180°, $r_S = 0.96$), and for the horizontal implementation of the model (225°, $r_S = 0.87$ and 180°, $r_S = 0.82$).

[9] http://azconservation.org/downloads/biotic_communities_of_the_southwest_gis_data

[10] http://www.mtbs.gov/data/customquery.html

[11] http://www.wilderness.net/NWPS/advSearch

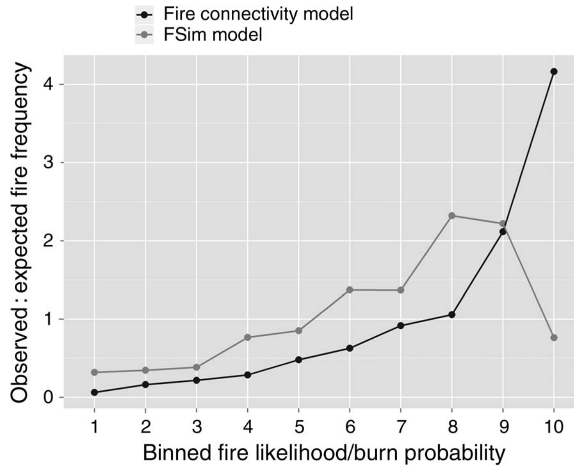

FIG. 2. The ratio of observed to expected (by chance) frequency of fire within 10 quantile bins of fire likelihood, for the fire connectivity model depicted in Fig. 4, and the FSim model of burn probability in our study area (Finney et al. 2011). Fire observations were derived from 2000–2012 moderate resolution imaging spectroradiometer (MODIS) burned area data. The ratio indicates a frequency of fire relative to chance. For the fire connectivity model, this ratio was increasingly greater than zero overall, and increasingly greater than one above the 80th percentile of predicted fire likelihood. For the FSim model, the ratio was greatest in the 80th percentile but decreased to below one in the highest bin, indicating that the highest burn probability over predicted actual fire occurrence.

By comparison, the FSim model for our study area offered somewhat less empirical support ($r_S = 0.72$). The ratio of observed to expected frequency of burned areas was greatest in the 80th percentile of burn probability, but decreased to below one in the highest bin (Fig. 2). This indicated that the highest FSim predicted probabilities actually burned less frequently than expected by chance. In contrast, the ability of our model to differentiate high fire likelihood from chance expectation increased within the 80th percentile of predictions (Fig. 2), providing strong support for our decision to use this percentile class to define HFL. Across the study area, 19% of predictions were classified as HFL, and of this area, 7% was estimated to have very high negative fire effects, 85% was estimated to have high effects, and 8% was estimated to have moderate effects.

We observed patterns of terrain-influenced winds on fire likelihood that substantially overlapped prominent topographic features in our study area, namely the numerous mountain ranges that are oriented in a southeast-northwest direction (Figs. 1 and 4). Considering simulated winds out of the southwest, areas most conducive to burning were consistently on the immediate windward side of mountain ridgelines, whereas areas least conducive were on the leeward side. Areas of intermediate fire likelihood were typically found in the valleys between these mountain ranges. Simulations based on winds out of the south showed similar patterns, although areas on the windward side of ridgelines

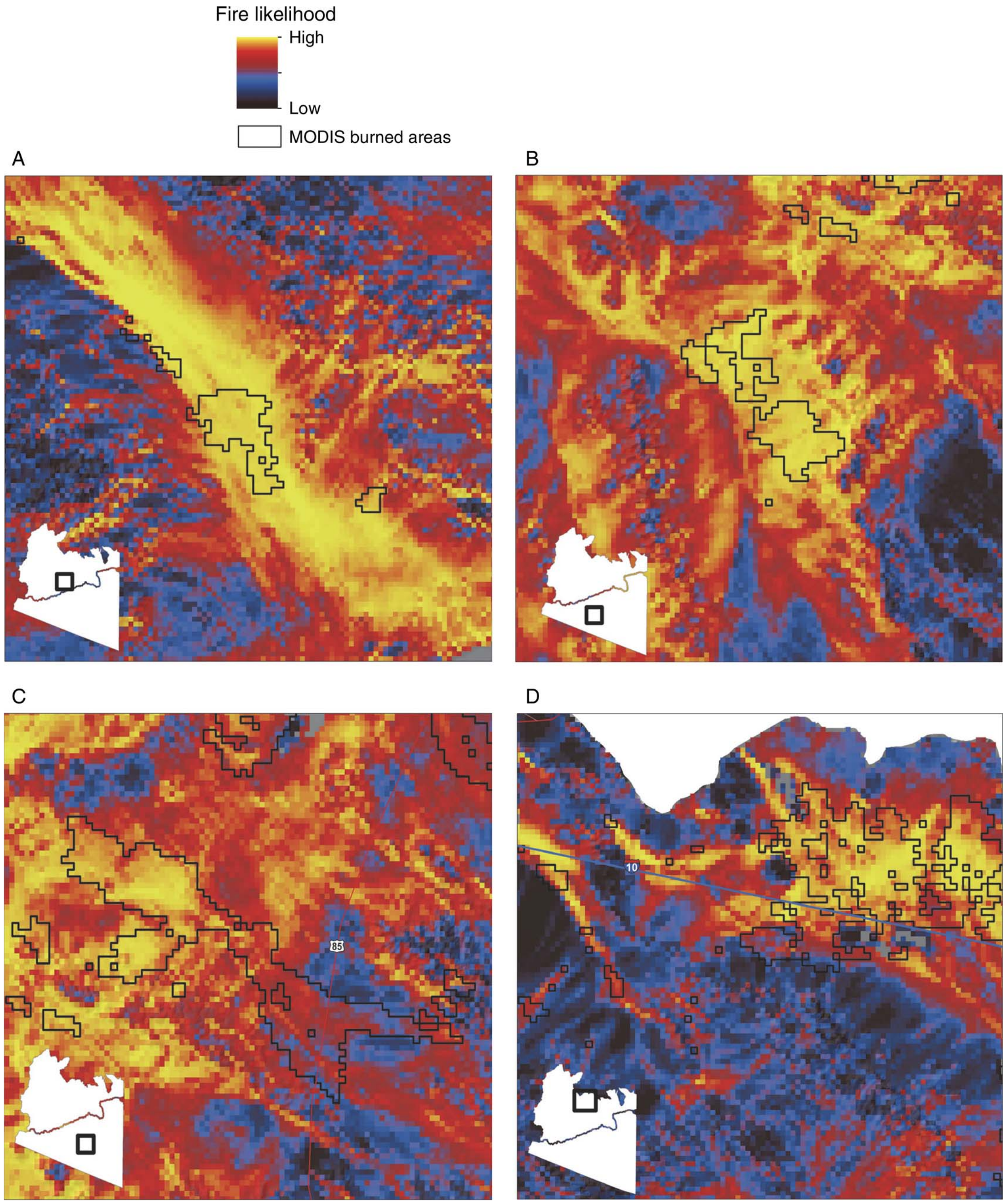

FIG. 3. Detail insets showing the agreement between estimates of fire likelihood and previously burned areas in four locations (shown in insets) of the lower Sonoran Desert: (A) King Valley Fire (see Plate 1), (B) Crater Fire, (C) Goldwater Fire, and (D) Bighorn and Eagle Eye Fire. These fires all burned in 2005, which was a year of unprecedented fuel growth and large fire occurrence in the lower Sonoran Desert.

showed lower fire likelihood. In general, HFL tended to disperse over larger areas where wind direction would most facilitate the spread of fire. In contrast, HFL tended to concentrate in narrow corridors, or completely avoid areas where dominant winds would move downslope. Across the study area, areas of HFL had an elevation of 295 ± 122 (mean ± SD), a slope of 6° ± 13°, and a mean topographic roughness (i.e., the standard deviation of slope) of 1.35 ± 2.90. In contrast, areas not characterized as HFL had an elevation of 396 ± 186 m, a slope of 8° ± 16°, and a topographic roughness of 2.12 ± 3.89.

Fire effects in Sonoran pronghorn habitat

HFL overlapped with 550 km^2 (21%) of suitable habitat in the current range of the Sonoran pronghorn

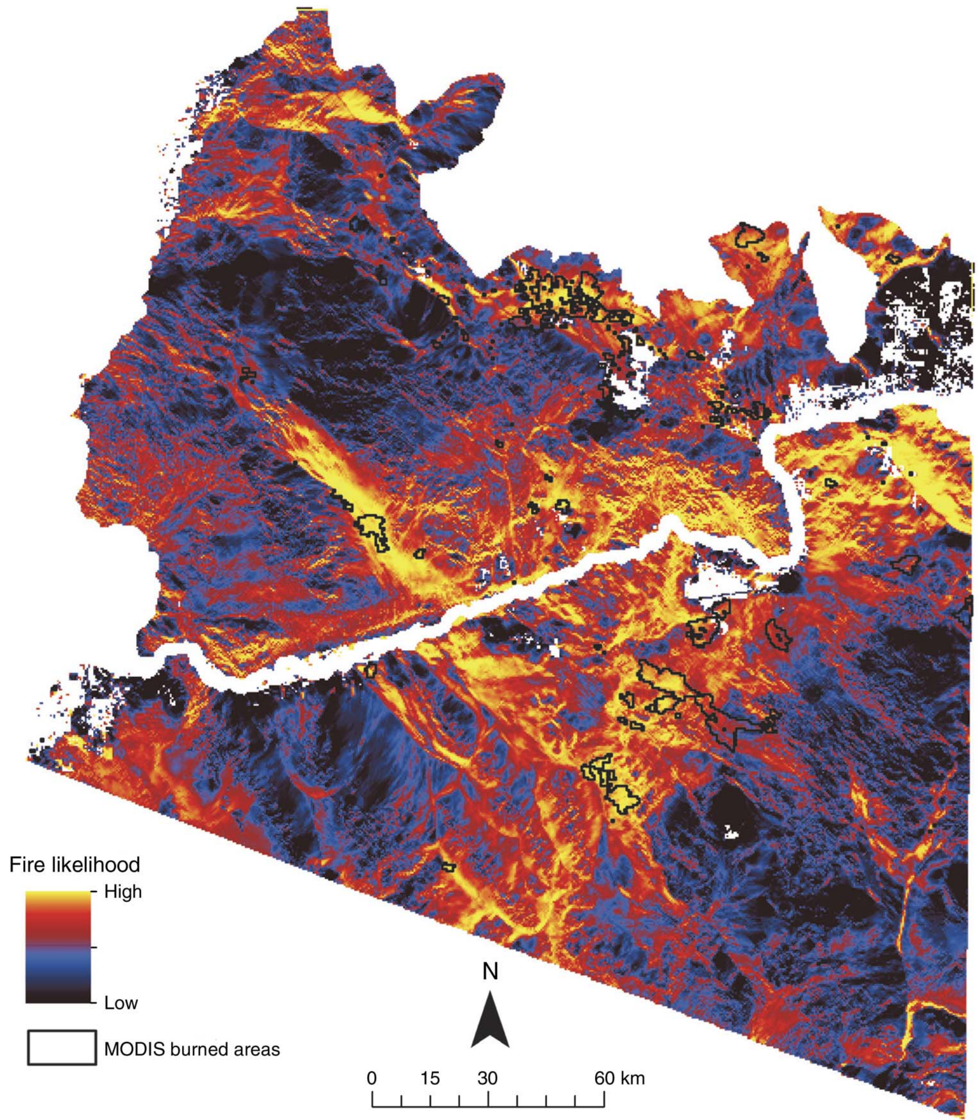

FIG. 4. Map of fire likelihood across the lower Sonoran Desert of southwestern Arizona, based on a circuit-theoretic model of fire connectivity. Warmer colors indicate relatively high current density, or higher likelihood of fire, and cooler colors indicate relatively low current density, or lower likelihood of fire. This map depicts a high fire hazard scenario of fire likelihood and is based on fuel conditions in 2005. Moderate resolution imaging spectroradiometer (MODIS) burned area data shows where fire occurred between 2000 and 2012.

(Fig. 5). Of this area, 8%, 91%, and 1% of HFL was estimated to have very high, high, and moderate negative fire effects, respectively. HFL overlapped with 3092 km^2 (15%) of the additional habitat considered suitable but not in the current range. 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. Large contiguous extents of additional suitable habitat that did not overlap with 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. 5).

Fire effects in wilderness

We estimated HFL in 1740 km^2 (14.5%) of the 16 wilderness areas within the study area (Fig. 6), with 19%, 74%, and 7% of HFL expected to have very high, high, and moderate negative fire effects, respectively. By total area HFL, the Cabeza Prieta (787 km^2) and Kofa (365 km^2) Wilderness areas were most at risk and expected to have high or very high effects. The areas of very high effects overlap with two of the largest fires that occurred in 2005, the King Valley fire (130 km^2; see Plate 1) in the Kofa Wilderness and the Growler Peak fire (110 km^2) in the Cabeza Prieta Wilderness. Similarly, HFL was estimated in large portions of the North Maricopa

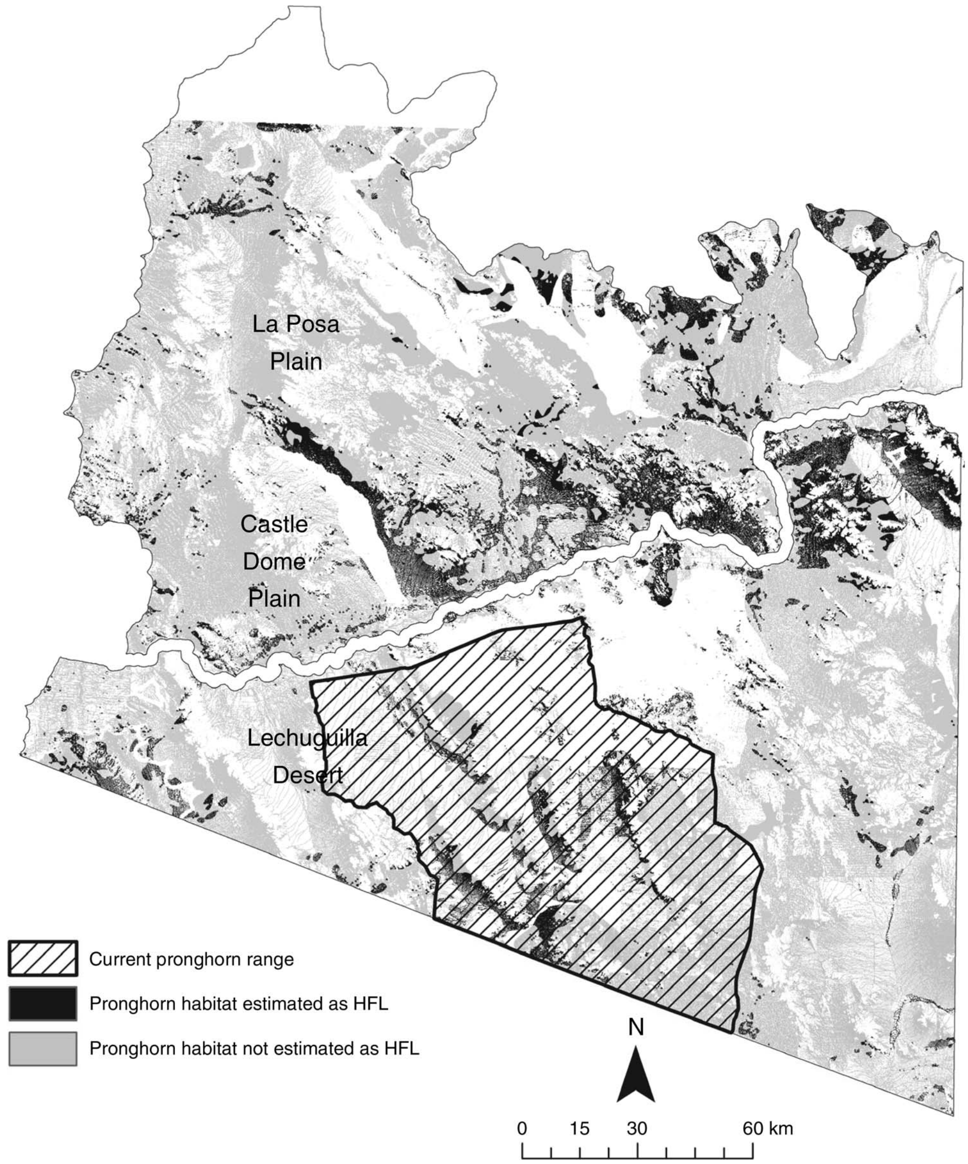

FIG. 5. Estimates of high fire likelihood (HFL) within the current range and potential habitat of the Sonoran pronghorn. Large areas of potential habitat not delineated as HFL may indicate sites suitable for ongoing or future translocations. Estimates are cut off in the northern tip of the study area because this was the extent of the original model of potential Sonoran pronghorn habitat (O'Brien et al. 2005).

Mountains (180 km^2) and Woolsey Peak (177 km^2) Wilderness areas, although much of these areas fall within the Arizona Upland subdivision and have not experienced a large fire event since 1984. The Muggins Mountain (49%) and the East Cactus Plain (47%) Wilderness areas had the highest percentage of HFL, with all of this area expected to have high effects. Only the New Water Mountains Wilderness was estimated to have no HFL.

DISCUSSION

Across extensive areas and multiple jurisdictions, resource and fire management efforts can benefit from fire likelihood analyses that account for the highly stochastic nature of fire spread (Miller and Ager 2013). Drawing on concepts from electronic circuit theory, we leveraged a well-established, probabilistic method to derive novel models and maps of fire connectivity, and to produce meaningful interpretations of fire likelihood. Our estimates of the likelihood that an area will burn contribute important information to the overall fire risk in a system, which does not neglect the fire contagion process. For instance, large fires in this region were found more likely to originate from ignitions occurring in lower elevations with rougher terrain (Gray et al. 2014). This pattern differs from results shown here,

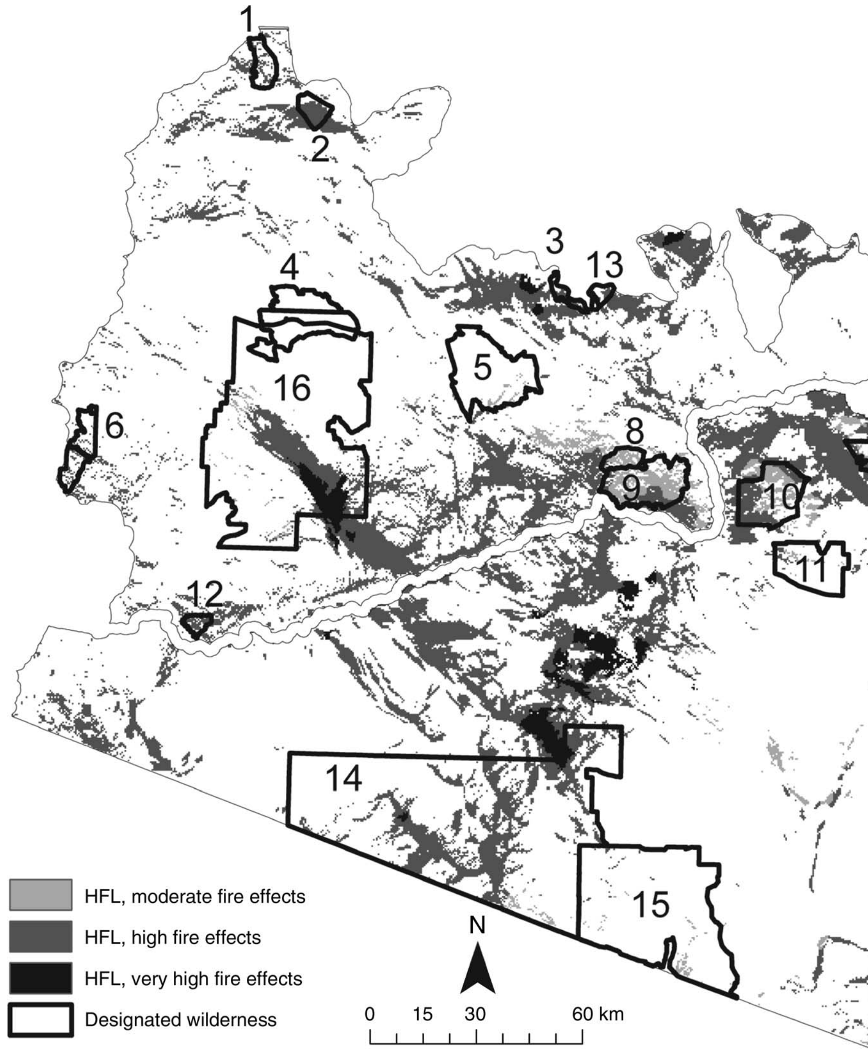

FIG. 6. Estimates of high fire likelihood (HFL) by fire effects level within 16 federally designated wilderness areas (some road corridors of non-wilderness have been removed for display purposes): (1) Gibraltar Mountain, (2) East Cactus Plain, (3) Big Horn Mountains, (4) New Water Mountains, (5) Eagletail Mountains, (6) Trigo Mountain, (7) Sierra Estrella, (8) Signal Mountain, (9) Woolsey Peak, (10) North Maricopa Mountains, (11) South Maricopa Mountains, (12) Muggins Mountain, (13) Hummingbird Springs, (14) Cabeza Prieta, (15) Organ Pipe, and (16) Kofa. HFL is defined as the 80th percentile of predicted fire likelihood under high fire hazard conditions. Effects are relative to the fire resilience and recent fire history of a given area.

where lower elevations and less rough terrain were more likely areas to actually burn. Desert wash systems are prominent micro-topographic features that weave throughout the lower elevations of our study area. It is likely that fires easily ignite in these densely vegetated washes but then more readily spread through fine fuels in the intervening, lower-relief terraces.

Our connectivity model further addresses the challenge of spatial scale in communicating and quantifying wildfire risk for management. The nearly infinite number of possible interactions between landscape features and weather conditions has been a major challenge to characterizing fire likelihood in large heterogeneous landscapes (Finney 2005). Monte-Carlo-based simulation methods that take advantage of extant fire spread models to efficiently estimate burn probability have gained considerable traction in the past few years because they address this challenge. Similarly, fire connectivity models embedded in a fire likelihood analysis offer new flexibility and efficiency in meeting fire management objectives, with some added advantages.

As a first step in our approach, we were able to capture the critical effect of annual fuel loads in a statistical model of large fire probability, which provided a reliable, empirically based scenario of high fire hazard for input into a fire connectivity model. Although this model captured only a snapshot in time, it represented a worst-case scenario in the recent past, reflecting conditions likely to become more common in the future with

PLATE 1. Abundant annual fuel growth in the winter of 2004–2005 led to several large fires throughout the study area in 2005, including the 13 000 ha King Valley fire pictured here (Sonoran Desert, Arizona, USA). Photo credit: Susanna Henry, U.S. Fish and Wildlife Service.

changing climate and fuels (Abatzoglou and Kolden 2011). As fuel conditions change due to large-scale wildfires or other disturbance events, the model could be re-run with, for example, updated projections of the maximum annual NDVI in an updated conductance surface. Resulting fire likelihood estimates would continue to be relevant to real, changing conditions important for fire and fuels planning. As a second step, this high fire hazard scenario was coupled with terrain-influenced winds to directly reflect the probability that a fire would "burn through" a conductor. After accounting for fire spread in all four cardinal directions and across the whole landscape, accumulated current density that passes through a conductor is equivalent to the overall fire likelihood. This is much different from a mechanistic model of fire spread such as FARSITE that burns through fuel models in a deterministic manner and is then used to estimate burn probability. In contrast, our method to estimate fire likelihood as a function of overall landscape conductance considered all possible pathways of fire spread across a broad, heterogeneous landscape. The cumulative output that combined scenarios of wind direction and source-target pairing outperformed each individual model run and offered much stronger empirical support than FSim burn probability estimates for our study area. The FSim model estimated some of the highest burn probabilities in the upland regions and over predicted actual fire occurrence in these areas. Our new approach to modeling fire likelihood is easily transferable to other ecosystems (e.g., forested ecosystems) where fuel models have not been reliably calibrated against empirical data or observations of fire behavior, or where a paucity of empirical data otherwise inhibits the parameterization of burn probability models.

Applying fire connectivity models to risk assessment and management

Our results can aid in the management of critical habitat features for sensitive or listed species, including the highly isolated and endangered Sonoran pronghorn. This species was listed as endangered by the U.S. Fish and Wildlife Service in 1967 and recovery efforts were recently reviewed in light of the Final Revised Recovery Plan of 1998 (U.S. Fish and Wildlife Service 1998), which had anticipated a down listing by 2005 (Wilson et al. 2010). Reproduction and resource use by the species are closely tied to seasonal precipitation events and access to high quality forage (Hervert et al. 2005). Although long term effects of fire on forage quality are not known, Sonoran pronghorn currently rely on a diversity of plant species that provide sources of water when primary forage has desiccated or is unavailable (Hervert et al. 2005). Therefore, efforts to expand their habitat should consider specific areas where this diversity is least likely to be threatened by fire dynamics, such as the three areas identified in our analysis.

Throughout the United States, designated wilderness areas also serve to protect wildlife habitat, rare and endangered species, watersheds, and the solitude that benefits both humans and non-humans alike (Scott 2004). Although wilderness lacks any direct development or degradation by humans, the indirect and external influences of humans can still impact natural conditions in these areas (Noon and Dickson 2004). The question of whether to actively manipulate fire within and around wilderness poses a serious dilemma for managers today (Cole 2001). Increases in nonnative fuel loads coupled with predicted changes in climate will likely challenge existing wilderness fire management policies in the lower Sonoran Desert (Miller et al. 2011). Our results indicated that the Kofa and Cabeza Prieta Wilderness areas in the lower Sonoran Desert may be particularly threatened by fire, as well as large portions of the Muggins Mountain and East Cactus Plain Wilderness areas. Developing and implementing viable response and mitigation measures for these areas should be a high priority for federal wilderness fire management.

Model uncertainties and limitations

Our model of fire likelihood was intentionally derived at relatively coarse spatial and temporal resolutions, and necessarily incorporates assumptions about many fine-scale processes. For example, the propagation of fire from one cell to another does not account for some explicit fire behavior characteristics. One such fire behavior is spotting, which causes accelerated growth by igniting spot fires far ahead of the main fire perimeter (Albini et al. 2012). Although the explicit incorporation of spotting behavior was beyond the scope of research, our connectivity model suggested strong overlap between areas of high fire likelihood and areas that had previously burned.

A related source of uncertainty comes from assigning relative conductance values to an inherently heterogeneous process (i.e., fire spread). Conductance to fire spread can potentially take on a range of values at any one location (or cell). 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. We believe that parameterizations of conductance values for modeling fire connectivity will be an active area of future research.

Next steps for estimating fire connectivity

Contemporary approaches to estimating landscape connectivity have great potential for improving the realism and application of fire modeling efforts. For example, the concept of centrality could be readily applied to future models of fire connectivity. Node centrality can be described as the importance of a node (e.g., a patch of contiguous fuel or a population center) to facilitating the movement of flow across a network (Freeman 1979), and in a circuit-theoretic model it is measured by considering all flow pathways between all pairwise combinations of nodes (e.g., Brandes and Fleischer 2005, Dickson et al. 2013). Fire connectivity models, such as ours, can easily be integrated into centrality analyses using available computer programs (see Carroll et al. 2012). Conceivably, these analyses could present a more complete picture of relative node importance, considering the complex topology of fuels, weather patterns, and fire spread, where unique nodes might represent expanding or future areas of nonnative plant invasion.

We also envision integrating modeled fuels and fire behaviors (e.g., rate of spread) into fire connectivity analyses. The minimum travel time algorithm is an efficient formulation of FARSITE that stores cumulative fire arrival times from an ignition source and identifies minimum-time contours to approximate fire growth (Finney 2002). A circuit-theoretic model of fire connectivity, where landscape conductance is proportional to fire rates of spread, could show comparable patterns of fire movement. However, the probabilistic (vs. deterministic) method of movement may be better suited to the stochastic nature of fire. Estimates of fire connectivity that are based on fuel models and fire behavior could potentially integrate fireline intensity to determine spotting and fire effects (Finney et al. 2011). Assuming reliable fuel models are available, this approach would also be transferable between forested and non-forested ecosystems.

The new approach we have presented to modeling fire likelihood has great potential to further the reach of landscape-scale risk analyses in wildfire applications, in multiple ecosystem types and management settings. From a fire and fuels modeling perspective, the lower Sonoran Desert is a highly dynamic and heterogeneous system, which adds to the challenge of quantitative risk analysis. As ongoing changes in climate and land cover are poised to alter the fire regime across extensive and ecologically important areas, fire and resource management in the lower Sonoran Desert is addressing the potential for increased likelihood of fire. Comprehensive and multi-jurisdictional planning efforts at a regional scale will be enhanced by fire risk analyses, which incorporate the overall likelihood of burning and potential fire effects.

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