Landscape Ecol
DOI 10.1007/s10980-016-0353-2

RESEARCH ARTICLE

Applying fire connectivity and centrality measures to mitigate the cheatgrass-fire cycle in the arid West, USA

Miranda E. Gray · Brett G. Dickson

Received: 13 April 2015 / Accepted: 26 February 2016

Abstract
Context Strategic placement of fuel treatments across large landscapes is an important step to mitigate the collective effects of fires interacting over broad spatial and temporal extents. On landscapes where highly invasive cheatgrass (*Bromus tectorum*) is increasing fire activity, such an approach could help maintain landscape resilience.
Objectives Our objectives are to 1) model and map fire connectivity on a cheatgrass-invaded landscape, as well as the centrality of large cheatgrass patches, in order to inform a landscape fuel treatment (i.e., a network of greenstrips); and 2) evaluate the modeled greenstrip network based on changes to cheatgrass patch centrality.
Methods Our analysis covers 485-km^2 on the Kaibab National Forest in Northern Arizona. We apply a circuit-theoretic model of fire connectivity between all pairs of large cheatgrass patches. Based on these results, we calculate a measure of centrality for each patch to inform fuel treatment placement. We evaluate the modeled greenstrip network by comparing the pre- and post-treatment centrality of each patch.
Results After modeling fire connectivity across the landscape, we identify 25 of 68 large cheatgrass patches with relatively high centrality. When we simulate greenstrips around these focal patches, model results suggest that they are effective in reducing the centrality for at least 19 of the 25 patches.
Conclusions Fire connectivity models provide robust network centrality measures, which can help generate multiple, landscape fuel treatment alternatives and facilitate on-the-ground decisions. The extension of these methods is well suited for landscape fuels management in other vegetation communities and ecosystems.

Keywords Fire connectivity · Centrality · Landscape fuels management · Cheatgrass · Invasive-fire cycle · Circuit theory · Fire likelihood · Fuel models

M. E. Gray (✉) · B. G. Dickson
Conservation Science Partners, Inc., 11050 Pioneer Trail, Suite 202, Truckee, CA 96161, USA
e-mail: miranda@csp-inc.org

B. G. Dickson
Lab of Landscape Ecology and Conservation Biology, Landscape Conservation Initiative, School of Earth Sciences and Environmental Sustainability, Northern Arizona University, Box 5694, Flagstaff, AZ 86011, USA

Introduction

In wildland fire and fuels management, landscape-level treatments aim to fragment fuels across a large landscape in order to lower the risk associated with large and potentially severe wildfires (Agee et al. 2000). For a variety of vegetation types, this management approach relies on fuel treatments at the local-

Published online: 14 March 2016

level that modify individual fire behavior, which are then "scaled-up" to modify the effects of fires interacting on the landscape over multiple years (Collins et al. 2010). For example, management objectives at the landscape-level may be to limit negative fire effects across a given landscape and time period using a network of strategically located treatments, each intended to create a fire-limiting canopy (Ager et al. 2013). The placement of fuel treatments is central to meeting these objectives, as some areas are predictably more likely to experience negative fire behavior and effects than others. Therefore, spatially explicit methodologies that allow practitioners to compare multiple fuel treatment placements, and that can be transferred across ecosystems with variable treatment objectives, are essential to landscape-level fuels management (e.g., Parisien et al. 2007; Moghaddas et al. 2010; Ager et al. 2011).

Across the arid regions of the Intermountain West, cheatgrass (*Bromus tectorum*) is a non-native, highly invasive annual grass that is facilitating changes in fire behavior and increases in fire activity (Balch et al. 2013). As increased fire frequency reduces the vigor of native vegetation and encourages further invasion, cheatgrass can begin to dominate post-fire vegetation communities (e.g., Whisenant 1989). When cheatgrass contributes to fire frequencies that far exceed historical fire return intervals, the invasive/fire cycle has established and it is ecologically and economically very difficult to restore landscapes (D'Antonio and Vitousek 1992; Brooks and Chambers 2011). Where cheatgrass has reached sufficient abundance to create new fuel conditions and alter fire behavior in localized patches, there is a critical need to manage against more widespread, homogeneous cheatgrass cover (Brooks et al. 2004). Identifying strategic mitigation or restoration activities requires a landscape-level perspective that considers the specific properties of cheatgrass fuels and associated fire behavior.

An intrinsic property of cheatgrass that can help drive changes in fire occurrence and seasonality is its positive response to variation in climatic conditions (Abatzoglou and Kolden 2011). Strong and ongoing interannual variability in precipitation and increased warming in arid climates will likely favor future increases in cheatgrass cover, even at its higher elevation ranges (Compagnoni and Adler 2014). Coupled with warmer temperatures, years of above-average winter and spring precipitation can lead to increases in cheatgrass biomass, which, in turn, can contribute to increased fire frequency in the following season (Balch et al. 2013). In arid landscapes, where native plant communities are typified by sparse cover, a more continuous canopy can also increase the rate of spread in some vegetation types, including pinyon-juniper associations (Balch et al. 2013). Notably, the fluctuations of biomass in arid landscapes can be leveraged to model dynamic fire risk over extensive areas by using, for example, the Normalized Difference Vegetation Index (NDVI) (Gray et al. 2014).

In the context of landscape-scale changes to fire dynamics, fire managers and planners must consider both the intrinsic properties of cheatgrass (e.g., its responses to climate) and the extrinsic properties introduced to native fuelbeds (e.g., its effect on fire spread rates). For instance, interannual variation in climate and fire hazard in cheatgrass-invaded landscapes will have a large influence on fire connectivity from year to year, and predictions of where fire is more likely to burn (Gray and Dickson 2015). Changing fire connectivity also influences the relative importance of large cheatgrass "patches" in facilitating fire spread through the greater landscape network. In a network analysis, centrality measures are important indicators that expose the key nodes for transmitting a specific flow process (e.g., fire spread) across the network (Borgatti 2005). Within a network of cheatgrass patches expected to increase the frequency and extent of fire, centrality measures might be determined for each patch, with the goal of determining its relative contribution to large fire spread. Specifically, betweenness centrality is a measure of the extent to which a node lies on the path between all others and facilitates flow across the whole network (see Newman 2005). Closeness centrality is a measure of a node's effective distance to all other nodes (see Brandes and Fleischer 2005). Centrality concepts have been widely applied in the context of landscape habitat connectivity (Bodin and Saura 2010; Theobald et al. 2012; Carroll et al. 2012), but they have never been applied in the context of landscape fire connectivity.

For the purpose of mitigating fire connectivity in a cheatgrass-invaded landscape, map-based predictions of connectivity and centrality will be most useful if they are based on an observed or forecasted distribution of high cheatgrass biomass, when the extrinsic properties of cheatgrass will exert their greatest influence on native fire regimes (Pausas and Keeley 2014). Planted strips of fire-resistant vegetation, i.e., "greenstrips," have been used as a mitigation tool to decrease overall flammability of a cheatgrass fuel complex and interrupt fire connectivity under hazardous conditions (Pellant 1989). In Arizona and Nevada, a number of experimental greenstrips have been planted to determine how best to combine greenstripping, seed coating technologies, and targeted grazing to control cheatgrass and fire in the western US (L. Porensky, pers. comm.). However, a landscape-level approach has never been applied to prioritize greenstrip placement. The methods and outcomes we present here can contribute to the strategic and cost-effective design of greenstrip networks across extensive areas.

In this paper, we apply a new modeling approach based on fire connectivity and centrality to guide greenstrip placement on landscapes where cheatgrass is causing abrupt changes to native ecosystems and fire regimes (Pausas and Keeley 2014). Our primary goals are to use the phenological and fuel-related properties of cheatgrass that distinguish it from native vegetation to model and map fire connectivity across a highly invaded landscape in northern Arizona, and to demonstrate how a greenstrip network can mitigate fire dynamics. Our specific research objectives are to: (1) map cheatgrass presence in a year of observed high abundance in order to predict the enhanced rate of fire spread across a heterogeneous landscape; (2) use these results to estimate and map fire connectivity and relative betweenness centrality among large patches of cheatgrass; and (3) demonstrate how strategic placement of greenstrips can then be modeled and evaluated based on changes to relative betweenness and closeness centrality.

Methods

Study area

Our 485-km^2 study area is within the North Kaibab Ranger District on the Kaibab National Forest in northern Arizona, on the western escarpment of the Kaibab Plateau (Fig. 1). Elevations range between 900 and 2000 m. Normal winter/spring (December–May) precipitation for the period from 1981 to 2010 ranged between 112 and 31 mm, annual maximum temperature ranged between 17 and 24 °C, and annual minimum temperature ranged between 2 and 8 °C (PRISM Climate Group, http://prism.nacse.org/normals/). Dominant vegetation associations include Colorado Plateau pinyon-juniper woodland and Inter-Mountain Basins Big Sagebrush shrubland. In 1996, the 21,500 ha Bridger Knoll fire burned 9000 ha of the study area. This fire facilitated a large-scale invasion by cheatgrass, and almost half of this area has reburned in subsequent years (see below), especially in patches of vegetation with high cheatgrass density. High fire activity in the past decade occurred in 2007 and 2012, in which approximately 4500 ha of the study area burned.

Mapping cheatgrass and fire rate of spread

Precipitation on the west Kaibab Plateau in the winter and spring of 2011 was above average and contributed to increased cheatgrass germination and growth. To detect cheatgrass based on its early season phenology, we acquired Landsat TM scenes from the spring of 2011 (May 3, 2011) and the beginning of summer 2011 (June 20, 2011), from the U.S. Geological Survey (USGS) Global Visualization Viewer (http://glovis.usgs.gov, accessed July 2013). These acquisition dates coincided as closely as possible with peak cheatgrass greenness in the spring and cheatgrass senescence by early summer, and also provided scenes that were completely cloud-free. We atmospherically corrected all images and obtained surface reflectance to derive NDVI values, using ENVI 4.7 software (Exelis Visual Information Solutions, Boulder, Colorado, USA). In a geographic information system (GIS; ArcGIS v10.1, Redlands, CA, USA), we created a 30-m resolution raster of the seasonal difference in NDVI (dNDVI), calculated as the spring NDVI minus the summer NDVI. We therefore expected that values increasingly greater than zero would indicate a more likely presence of cheatgrass (Bradley and Mustard 2005). To determine the dNDVI values that best discriminated the presence of cheatgrass in 2011, we drew opportunistically on a cheatgrass cover dataset that was collected in the early summers of 2005 and 2011, as part of a larger ecosystem assessment of the Kaibab Plateau (Sisk et al. 2010). The sampling protocol for this assessment used a randomized design stratified on soil and vegetation type, in circular plots of 168 m^2. Cheatgrass cover for the plot was estimated

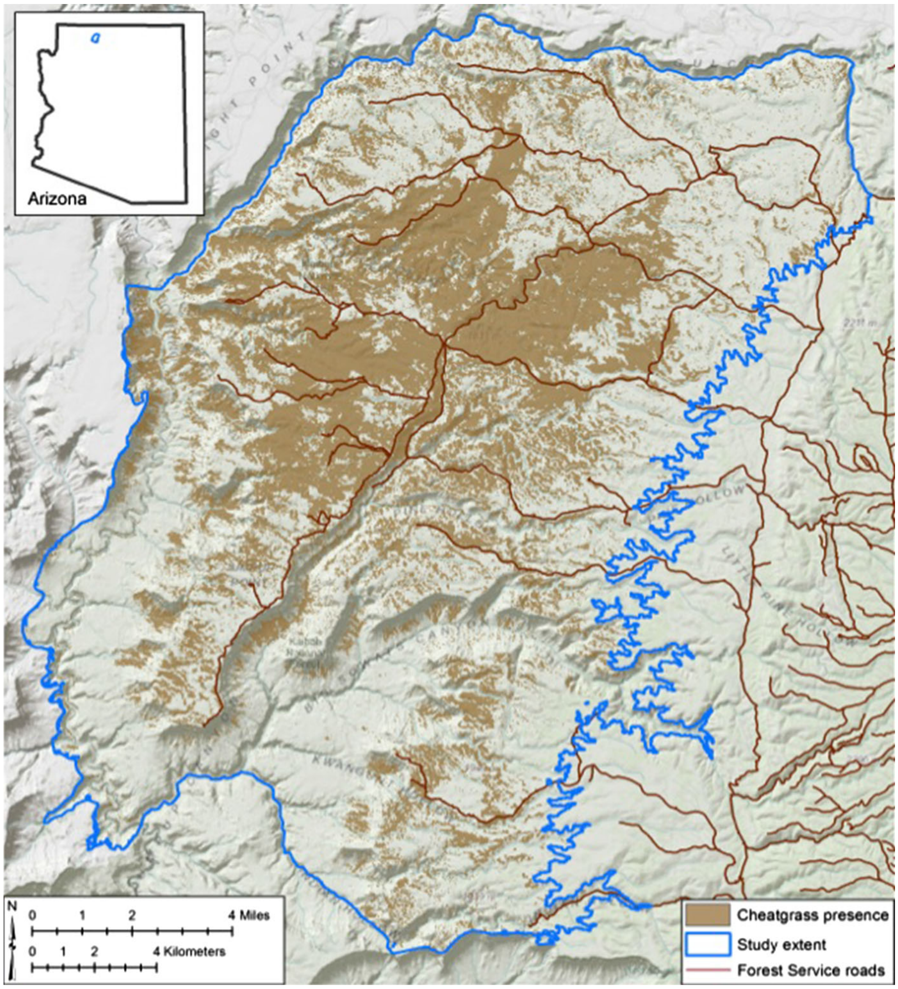

Fig. 1 Predicted cheatgrass presence based on the difference in Normalized Difference Vegetation Index (dNDVI) values between spring and summer 2011. Cheatgrass displays an earlier green-up and senescence from native vegetation in the study area that can be detected using dNDVI thresholds

as the average cover taken across nine, one square-meter subplots. Sixty-three of the plots were sampled in 2005, and another 36 plots were sampled in 2011. As was the case in 2010–2011, precipitation in the winter and spring of 2004–2005 was also above average.

With these 99 samples, we considered cover <1 % to be cheatgrass "absence" and >1 % as "presence." Sixty-two of the 99 plots contained a trace amount of cheatgrass cover (<1 %), whereas only eight of the plots had strictly zero cheatgrass cover. Classifying presence and absence with a 1 % breakpoint allowed for a more balanced sample size while retaining sufficient samples in each class. This breakpoint for defining presence and absence has also been used in other locations to detect cheatgrass with Landsat imagery (see Clinton et al. 2010). Using the Raster (Hijmans and van Etten 2012) and ROCR (Sing et al. 2005) packages in R 2.15.1 (R Development Core Team 2011), we extracted the dNDVI values at each plot location and statistically related them to the binary estimates of presence or absence. We calculated the area under the receiver operating characteristic (ROC) curve (AUC) to provide a measure of how well the dNDVI method discriminated between presence and absence (Hosmer and Lemeshow 2000). For the purposes of classification, we determined the dNDVI threshold value that maximized the true positive rate of cheatgrass detection, while minimizing the false positive rate. Since results based on this decision could direct the use of limited management resources, we chose to err on the side of a conservative detection rate. We therefore assumed that a false positive was twice as costly as a false negative. We calculated the ROC and used a cost function (https://github.com/joyofdata/joyofdata-articles/blob/master/roc-auc/calculate_roc.R) to help determine the optimal dNDVI threshold value in this case (Pontius and Parmentier 2014). Using the GIS, we reclassified dNDVI to a binary raster, where values greater than the threshold were estimated as presence, and values less than the threshold were estimated as absence.

To account for the increased rate of spread caused by cheatgrass fuels, we used the presence/absence cheatgrass map to update standard fire behavior fuel models (FBFM; Scott and Burgan 2005) based on observed fire spread in 2012. We looked specifically at three large fires that occurred in our study area in 2012 (Table 1), since detailed fire growth and suppression information was available for these fires from Incident Status Summary (IC-209) reports (http://famtest.nwcg.gov/fam-web/, accessed October 2013) and from the Incident Information System (http://www.inciweb.nwcg.gov, accessed October 2013). We also know from IC-209 reports that these fires burned through cheatgrass fuels, in native brush and pinyon-juniper communities. The FBFM and topography data (30-m resolution) were obtained from the LANDFIRE project (http://www.landfire.gov, accessed October 2013). The FBFM included characteristics of surface and canopy fuels, in formats required by fire growth and behavior simulation software, including FARSITE (Finney 2004) and FLAMMAP (Finney 2006). FARSITE simulates fire growth under hourly weather conditions and can be used to reconstruct historical fire growth for fuel model calibration (Stratton 2006). In addition to the FBFM and topography data, we parameterized FARSITE with ignition data from the Kaibab National Forest (http://www.fs.usda.gov/detail/r3/landmanagement/gis/?cid=stelprdb5209305, accessed September 2013), weather and fuel moisture data from the Gunsight RAWS weather station (http://www.raws.dri.edu/, accessed October 2013), and fire suppression information from the Incident Information System. We assumed burn periods of 10:00–18:00 and simulated durations that coincided with fire progression data from the IC-209 reports. We simulated the three fires under real-time weather to see how well the "off-the-shelf" FBFM approximated fuels that were actually affecting fire spread rate. IC-209 reports indicated that a low-load, dry climate grass was the primary carrier of fire. Therefore, we used the GIS to

Table 1 Incident summary information for three large fires that were simulated in FARSITE and used to calibrate cheatgrass fuel models on the west side of the Kaibab Plateau

Parameter	Fire name		
	EAST	TANK	JUMPUP
Fire duration	08/09/12 10:00 to 08/10/12 15:00	07/21/12 12:30 to 07/22/12 18:00	08/13/12 14:55 to 08/14/12 14:00
Fire size (ha)	790	1030	145
Dominant wind directions	SW and SE	E and SW	S
Peak wind gusts (km/h)	10	13	24
Maximum temperature (°C)	38	36	34
Minimum relative humidity (%)	11	13	17
Initial 1-h fuel moisture (FM)	3	5	3
Initial 10-h FM	4	5	3
Initial 100-h FM	7	7	6
Initial live herbaceous FM	36	34	31
Initial live woody FM	82	65	77

All three fires burned through dense stands of cheatgrass, interspersed with native shrub, grasses, and pinyon-juniper vegetation. Incident reports indicated that the fires were at least 80 % contained and had reached 90 % of their final fire size by the time indicated on the second day. Thus, we assumed that suppression activities outweighed ambient environmental influences on fire growth and we ended simulations at this time reclassify cheatgrass presence as a GR2 fuel model across the whole study extent. Although shrubs and trees may be present, grass is the primary carrier of fire in the GR2 fuel model (Scott and Burgan 2005). Leaving all other fuel models unchanged, we re-ran fire simulations in FARSITE to see how well the updated FBFM approximated the fuels present in 2011.

With the updated fuels map, we then calculated potential rate of fire spread across the whole study extent. For this step, we used FLAMMAP (v.5), which simulates landscape fire behavior based on spatially varying winds (given an initial direction and speed), topography, and fuel characteristics. FLAMMAP outputs are isolated representations of the potential fire behavior at each landscape grid cell, and can be used to effectively compare relative rates of spread across the landscape, without actually simulating fire spread (Finney 2006). In addition to the updated fuels map and topography data, we parameterized FLAMMAP with wind and fuel moisture values. Diurnal wind summaries for June, July and August showed that winds were most frequently out of the south/southwest, and observed wind speeds reached 30 kmh. To estimate fire spread rates under high wind conditions, we used 180° winds at 30 kmh. Similarly, to estimate fire spread in low fuel moisture conditions, we used fuel moistures of the lowest 97th percentile recorded at the GUNSIGHT station. These were 3, 3, 4, 30, and 51 % for 1, 10, 100 h, live herbaceous, and live woody fuels, respectively. The final FLAMMAP output was a 30-m resolution raster dataset that estimated the potential rate of spread at each grid cell, taking into account fuels, weather, and topography, but not the influences of neighboring pixels. Circuit theory models integrated the FLAMMAP output to simulate fire spread and estimate fire likelihood across the landscape (see below).

Fire connectivity modeling and greenstrip placement

In addition to using the cheatgrass presence/absence map to estimate rates of fire spread across the landscape, we used the map to identify relatively large patches of cheatgrass presence. We used the GIS to determine if cheatgrass presence (vs. absence) was dominant in a 10-ha radius. We then retained patches >10 ha, because the small percentage of fires in our study area that have reached this size have often grown much larger. For instance, since 1930 only 12 % of recorded fires ($n = 173$) have reached 10 ha, and of these, 50 % grew to over 50 ha. To estimate the connectivity of fire between cheatgrass patches and under enhanced rates of spread, we used a circuit theoretic model of landscape connectivity (McRae et al. 2008). In order to estimate the likelihood of fire spread as a result of dynamic interactions with the environment, the landscape is modeled as a circuit network of connected conductors (Gray and Dickson 2015). In contrast to deterministic fire spread algorithms that have the rate of spread at their core (e.g., Finney 2002), circuit theory estimates the highly stochastic nature of fire spread. We used the FLAMMAP rate of spread estimates as a proxy for landscape conductance (i.e., the ability of the landscape to facilitate the spread of fire), such that each cell in our raster map was represented in the circuit model as a node connected by conductors to its eight nearest neighbors. Current (or analogously, fire) spreads through the circuit network in proportion to the eight conductance values at each node. The resulting current density at each node is equivalent to the net, directionless likelihood that fire will pass through that node, when spreading from a source to a target (i.e., the fire likelihood; Gray and Dickson 2015).

We implemented our fire connectivity model using Circuitscape software (v3.5.8; www.circuitsape.org). In order to estimate connectivity between all possible pairs of cheatgrass patches (i.e., "pairwise connectivity," see McRae et al. 2008), we initialized a source patch with 1 A of current and iteratively designated every other patch as the target. By assuming that fires start only within cheatgrass patches, we ignored other factors that potentially contribute to large fire ignition (e.g., lightning density and proximity to roads). However, across arid regions of the Western US, large fires have historically been more likely to start in cheatgrass-invaded areas compared to other, non-invaded land cover types (Balch et al. 2013). Therefore, this assumption was grounded in our objective to estimate the increased fire connectivity caused by cheatgrass fuels. From the pairwise model implementation, we retained only the maximum current density map, which tends to better reflect the current density between patches in relatively close proximity

(Dickson et al. 2013). This decision was intended to identify the most likely spread pathways between patches that were closer together.

In addition to identifying intermediate areas on the landscape that have a high likelihood of burning, the pairwise calculation also allowed us to derive two centrality measures for cheatgrass patches. Drawing on the definitions of centrality from network theory, betweenness centrality in this context measures the extent to which a patch facilitates the spread of fire across the whole landscape, and closeness centrality measures the patch's effective distance to all other patches. We determined relative betweenness patch centrality by summing the cumulative current density (i.e., resulting from all pairwise calculations) within each patch, normalized by area as an area-weighted measure of centrality (Dickson et al. 2013). We determined relative closeness centrality for each patch by taking the mean effective distance to all other patches. In circuit networks, distance is measured by the "effective conductance," which accounts for the cumulative conductance of all possible flow paths between patch pairs, and reflects the ability of fire to spread between those pairs (McRae et al. 2008). We used only the betweenness centrality measure to inform where on the landscape to simulate fuel treatments, whereas we used the betweenness and closeness measures to evaluate the modeled, post-treatment outputs.

Using the maximum current density map and the relative betweenness centrality of patches, we focused in on three areas of the landscape that would warrant active mitigation through the placement of greenstrips. The area-weighted betweenness centrality of patches was a primary indicator of where to focus these efforts, whereas the identification of "pinch-points" between focal patches was a secondary measure (McRae et al. 2008). This way, greenstrips would be located to most effectively interfere with fire connectivity between patches with a relatively high likelihood of contributing to fire spread. To make it easier to identify likely pinch-points, we reclassified the maximum current density map into 10 quantiles and focused primarily on the 80th percentile of estimates. We used a roads layer from the Kaibab National Forest to help locate more strategic placement of greenstrips that might buffer or adjoin existing roads. We used a 10-m elevation model to locate greenstrips on ridgelines wherever possible, and also considered placement in relation to dominant winds out of the south and southwest. We assumed that the short, sparse dry climate grass FBFM (GR1) could represent the fuel targets achieved by a greenstripping treatment, since spread rate and flame length are low compared to other GR models (Scott and Burgan 2005). Therefore, we converted the FBFM in these greenstrips to GR1 and re-implemented our connectivity analysis, leaving all other model parameters unchanged. In all cases, a greenstrip was one grid cell in width (i.e., 30 m) simply to demonstrate the resultant changes in centrality by converting a minimal area. This is also consistent with the width of greenstrips that have been implemented in the past (Pellant 1992). We used these simple guidelines to demonstrate a single application of a greenstrip network. Other specific design considerations of greenstrips, as well as resource constraints to otherwise guide greenstrip size and location, were beyond the scope of our research. To evaluate resultant changes in centrality, we looked at the difference between the pre- and post-treatment relative betweenness and closeness centralities for each focal patch.

Results

Cheatgrass presence and fire rate of spread

The ROC curve and associated cost function identified an optimal dNDVI threshold value of 0.037 (Fig. 2). Therefore, values ≥ 0.037 were classified as cheatgrass presence in the cheatgrass distribution map, and values <0.037 were classified as absence (Fig. 1). This threshold value resulted in a 65 % true positive rate of cheatgrass detection, a 15 % rate of false positive detection, and an AUC of 0.74. Because we did not withhold any data for evaluation purposes, our estimates of classification accuracy and AUC are likely inflated.

FARSITE model runs resulted in hectares where the simulation agreed with the actual fire perimeter (i.e., "hits"), hectares where the simulation failed to burn inside of the actual fire perimeter (i.e., "misses"), and hectares where the simulation burned outside of the actual fire perimeter (i.e., "false alarms"). Using an "off-the-shelf" FBFM, two of the simulations under- predicted area burned by at least four times the actual amount, and one simulation only slightly overpredicted the actual area burned. The Jumpup

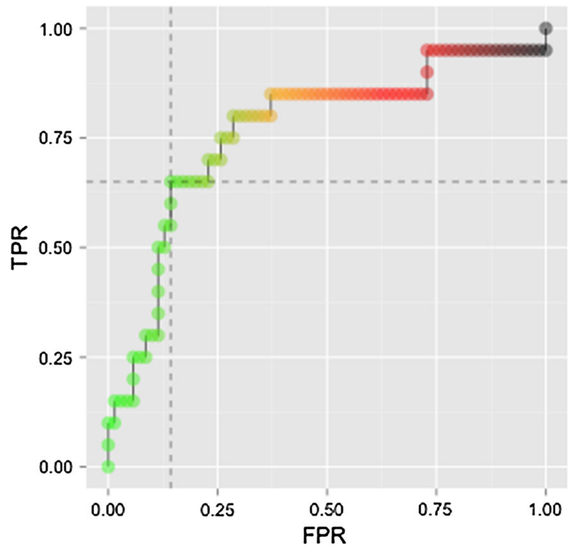

Fig. 2 ROC curve showing points that correspond to all possible threshold values of the dNDVI. Coloring of the points illustrate the associated cost (*green* low cost, *red* high cost) of the corresponding threshold value, and the dashed line represents the chosen threshold value (0.037) that simultaneously optimized the FPR and TPR. (Color figure online)

Fire resulted in 81 hits, 67 misses, and 14 false alarms; the Tank fire resulted in 814 hits, 217 misses, and 343 false alarms; and the East fire resulted in 278 hits, 515 misses, and 49 false alarms (Fig. 3). In all three of these simulations, FBFM were predominantly classified as the GR1 model. Using the updated FBFM, which accounted for a higher and more continuous fuel load where cheatgrass was present, simulations were more spatially consistent with observed fire perimeters but consistently overpredicted the area burned by at least six times the actual amount. The Jumpup fire resulted in 141 hits, 6 misses, and 53 false alarms; the Tank fire resulted in 1,010 hits, 21 misses, and 374 false alarms; and the East fire resulted in 753 hits, 40 misses and 263 false alarms (Fig. 3). In these simulations, fire progression in day one for all fires was especially consistent with actual fire perimeters.

The potential rate of spread estimated with the updated fuels map (i.e., the landscape conductance estimated with FLAMMAP) ranged between zero (FBFM NB9) and 185 m/min (FBFM SH5; Scott and Burgan 2005) across the study area. Mean spread rate for the GR2 model was 36 m/min (SD = 10). Other dominant fuel models in the study area were GS1 (0.3 m/min, SD = 2), GS2 (19,10), NB9 (0,0), GR1 (3,4), and SH1 (10,2) (Scott and Burgan 2005). We identified 68 unique cheatgrass patches that ranged in size from 10 ha to 9600 ha (mean = 185 ha, SD = 1,153 ha). The largest contiguous patch encompassed part of the fire perimeter of the 1996 Bridger-Knoll fire that re-burned in the 2007 Slide fire. Other patches coincided with past fire perimeters of the Faver fire (2012), Elbow fire (2012), Ranger fire (2012), East fire (2012), Tank fire (2012), Jumpup fire (2012), and Snake fire (2005).

Pre and post-treatment fire connectivity

The map of relative betweenness patch centrality (Fig. 4) exposed focal areas of cheatgrass cover that were most important for facilitating fire spread when all patch pairs were iteratively connected. The area-weighted estimates revealed patches that were at a higher likelihood of burning than would be expected by size alone, while more likely contributing to the spread of fire across the landscape. Patches with the highest relative betweenness centrality were in the southern part of the study area, around Jumpup Point, and on the plateaus north and south of Big Sowats Canyon. These were all of intermediate patch size (~100 ha), whereas the largest contiguous patch covering the Slide and Bridger Knoll fires (9600 ha) suggested only intermediate betweenness centrality.

Our estimates and map of maximum fire likelihood between patches highlighted possible pinch-points for fire connectivity among all patch pairs, due to the underlying influences of fuels, topography, and winds (Fig. 5). To model the placement of greenstrips, we focused only on those pinch points that emerged among 25 patches of highest relative betweenness centrality in the southern portion of the study area (see Fig. 4). Around Jumpup Point, we located 21 potential greenstrips around 14 cheatgrass patches (Fig. 6d). North of Big Sowats Canyon, we located 3 greenstrips around 5 cheatgrass patches (Fig. 6c), and we located 8 greenstrips around 6 cheatgrass patches to the south of Big Sowats Canyon (Fig. 6b). The greenstrips encompassed a total area of 170 ha, or 0.3 % of the landscape. When fuels in these greenstrips were replaced with the GR1 FBFM, 19 of the 25 high centrality patches decreased in relative betweenness centrality (Fig. 7), and relative closeness centrality decreased or remained unchanged for all patches in the study area (Fig. 8).

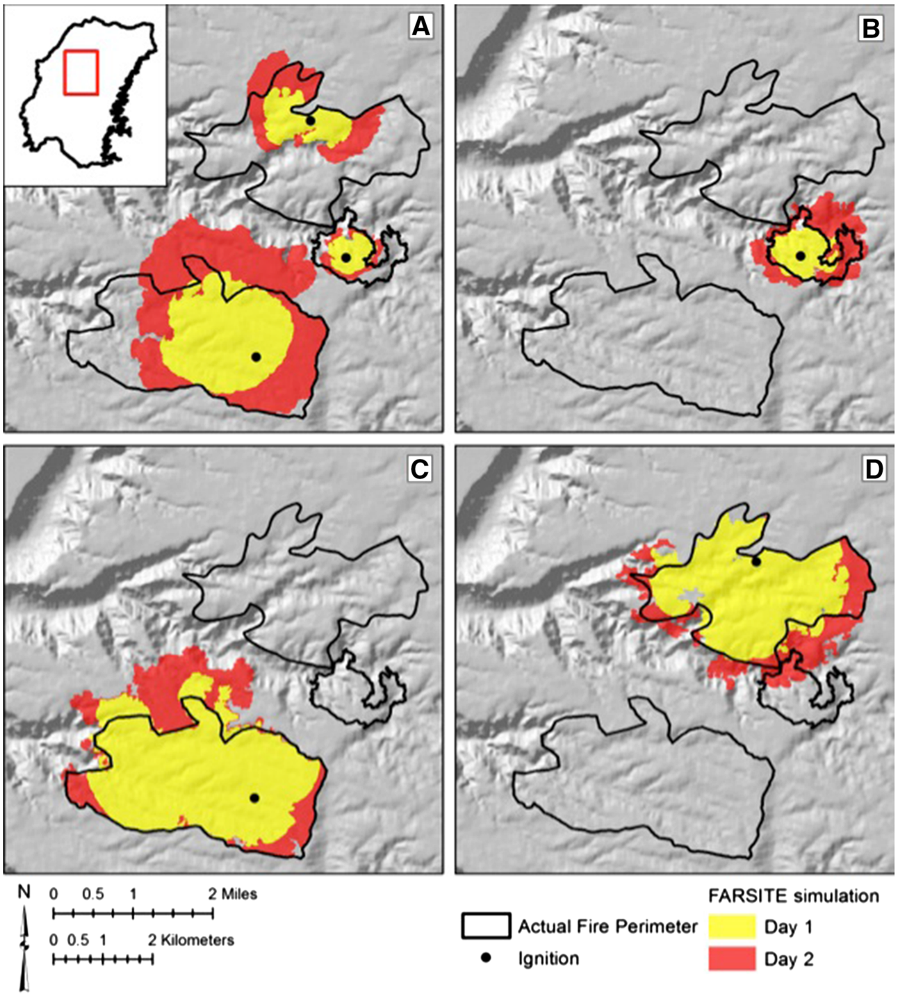

Fig. 3 FARSITE simulations for the three fires depicted in Table 1. **a** All fire simulations using 'off-the-shelf' standard Fire Behavior Fuel Models (FBFM; Scott and Burgan 2005); **b** Simulation of the Jumpup fire using a low load, dry climate grass fuel model for areas with predicted cheatgrass presence; **c** Simulation of the Tank fire using fire a low load, dry climate grass fuel model for areas with predicted cheatgrass presence; **d** Simulation of the East fire using a low load, dry climate grass fuel model for areas with predicted cheatgrass presence. Simulations with the updated fuels map resulted in more hits and less misses for all fires, but also more false alarms

Discussion

The strategic placement of fuel treatments to reduce fire risk across forested and non-forested ecosystems is an important step towards landscape fuels management and the mitigation of negative fire behavior and effects. Particularly in arid shrublands and woodlands, increased continuity of cheatgrass cover can inhibit the natural re-seeding of native vegetation after fire and lead to even more continuous cheatgrass fuelbeds in a post-fire landscape (Whisenant 1989). Once cheatgrass patchiness is virtually eliminated, the invasive/fire cycle leads to more frequent and larger fires and allows cheatgrass to dominate the landscape. Like many shrublands and woodlands throughout the western US, future climatic conditions in our study area are likely to remain suitable for cheatgrass invasion, making restoration efforts extremely difficult (Bradley 2009). Therefore, a foremost fire management objective for a cheatgrass-invaded landscape should be to maintain patchiness. This can be achieved with the strategic placement of greenstrips that slow or

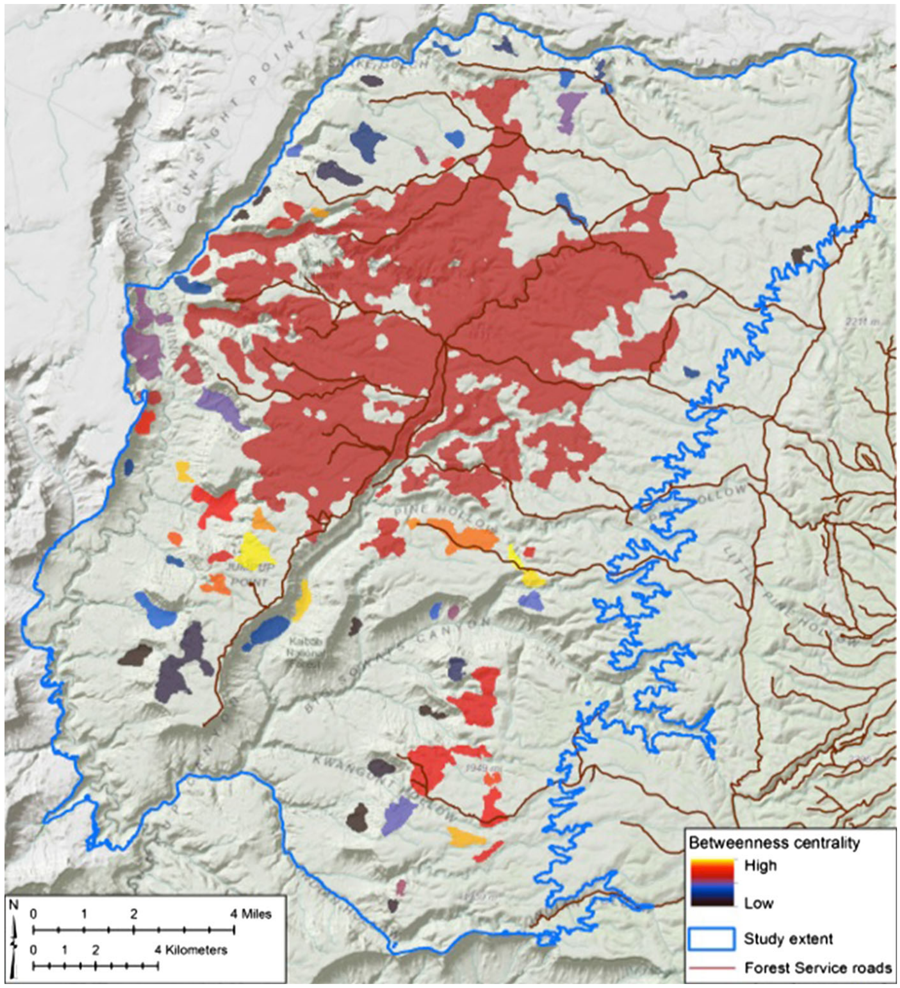

Fig. 4 Cheatgrass patches and associated area-weighted relative betweenness centrality estimates across the west side of the Kaibab Plateau. The *yellow* and *red* colored cheatgrass patches were predicted to be the most important patches for facilitating fire spread, *while black* and *dark blue* patches were predicted to be the least important. (Color figure online)

stop fire spread between cheatgrass patches and into intact native vegetation.

With limited resources to dedicate across large landscapes, it is necessary to understand where mitigation projects will be most ecologically and economically effective. Our landscape-scale models and maps of fire connectivity directly address this issue. To begin, we used cheatgrass cover data that was collected in the field to relate seasonal differences in NDVI values to cheatgrass presence. Based on comparison with the field data, our map was a conservative estimate of cheatgrass presence (i.e., it resulted in a low true positive rate). From an economic standpoint, maintaining a low false positive rate will help direct limited resources to locations with more certainty. From an ecological standpoint, we would expect false negatives to have lower actual cover than true positives, since the subtle difference between zero and 1 % cover in remotely sensed imagery is not easily discernible. Here we were also more willing to accept a lower false positive rate at the cost of a higher false negative rate.

Without accounting for the predicted cheatgrass presence in fuel models, two out of three fire simulations underpredicted actual fire spread, suggesting that cheatgrass cover was indeed missing from these models. In the simulation where fire spread was slightly overpredicted, the number of misses was twice the number of hits, indicating poor spatial overlap with the actual fire perimeter and, again, a misspecification of the fuels map. After replacing areas of predicted cheatgrass presence in 2011 with a dry climate grass fuel model, simulations of fires that occurred in 2011 closely replicated the observed fire perimeters, despite

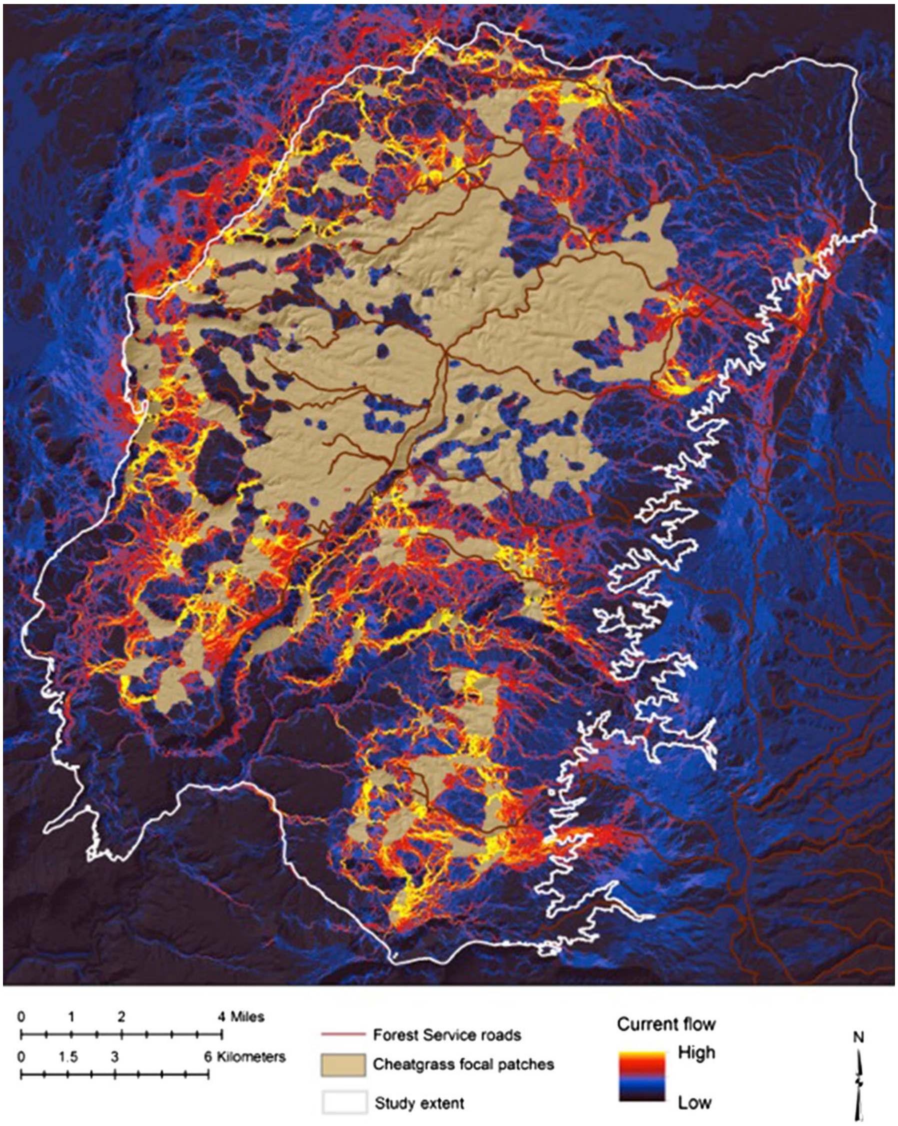

Fig. 5 Highest likelihood fire spread pathways between cheatgrass patches (*yellow* high likelihood, *black* low likelihood) across the west side of the Kaibab Plateau. Fire spread pathways were derived by modeling the connectivity between all possible pairs of cheatgrass patches using the program Circuitscape (v3.5.8; www.circuitsape.org). 'Pinch-points' are located along the narrow paths of highest fire likelihood. (Color figure online)

some overpredicting of the area burned. This makes sense considering we replaced cells with >1 % cover of cheatgrass with a uniform fuel model in which fuel composition parameters, including fuel loading, remain fixed across space. Indeed, a model of absolute fire behavior should be interpreted with caution because the true variability of weather, fuels, and topography is likely manifest at a finer spatial grain size. However, when results are used to compare relative fire behavior under a common weather scenario, they provide an excellent basis to analyze connectivity under alternative fuel conditions and treatments (Fulé et al. 2001).

Ideal targets for mitigation would be those cheatgrass patches that are expected to contribute most to fire connectivity between other patches and across the landscape. We used robust measures of centrality to rank cheatgrass patches based on their relative importance in facilitating fire spread between all patch pairs. The largest patch, which included the burned extent of the 1996 Bridger-Knoll fire, should have resulted in the greatest cumulative fire likelihood. However, many smaller patches in the southern portion of the study area each revealed a larger area-weighted betweenness centrality. Thus, we chose to focus on these areas to illustrate how the existing

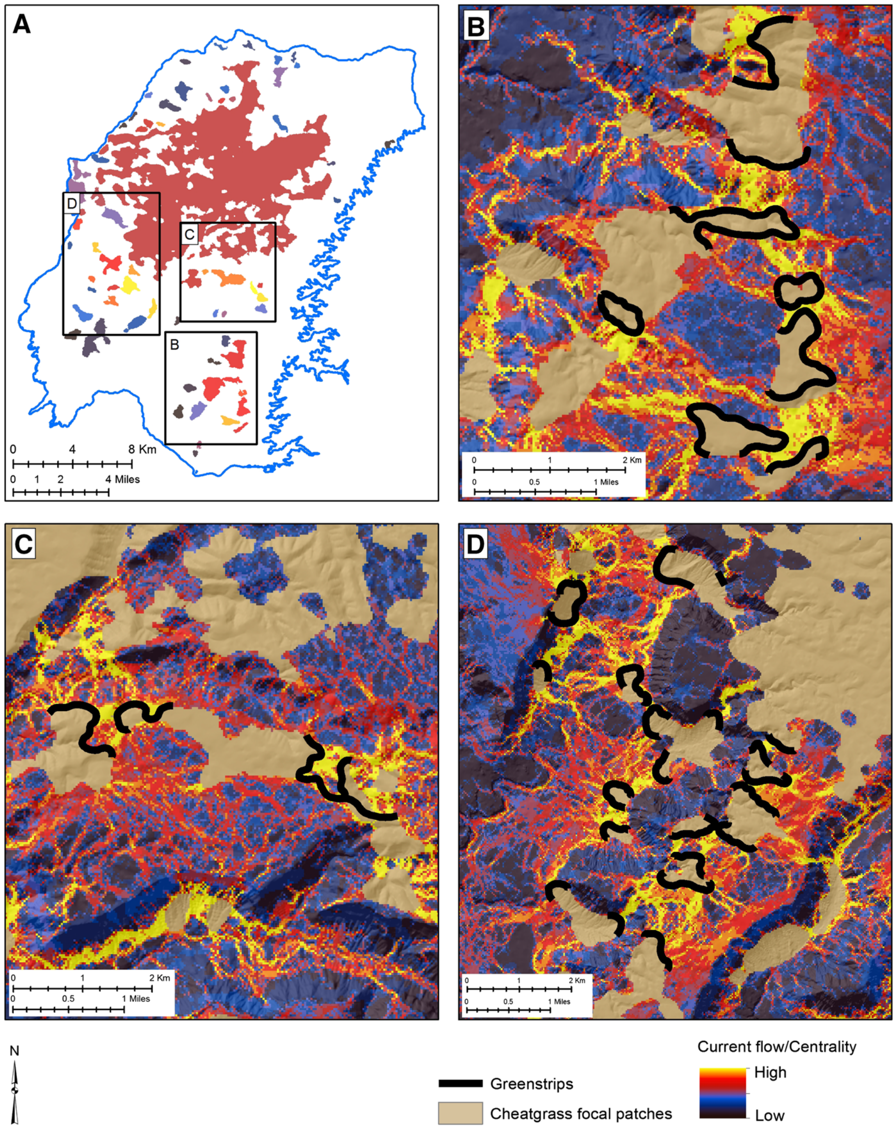

Fig. 6 Location of potential greenstrips in three different areas on the west side of the Kaibab Plateau. Greenstrip placement was determined by the relative area-weighted betweenness centrality of patches and the presence of predicted 'pinch-points' between focal patches

patchiness might be maintained through the restoration of fire spread and behavior. A more detailed analysis of fire connectivity and fuel treatment placement would likely be warranted within the Bridger-Knoll patch, due to the continuous extent of cheatgrass invasion in that area. Indeed, our estimates of relative centrality are based on values of current density that could be readily used to explore within-patch patterns of fire connectivity.

Models of fire behavior provided a basis to examine the relative change in connectivity under a hypothetical arrangement of greenstrips on our focal landscape. Since all parameters except fuel type remained the same between our two connectivity scenarios, it was simple to compare the change in relative centrality by looking at differences in current density and effective conductance. With one such network, in which only 0.3 % of the landscape was converted to a low load dry climate grass model, our results showed an overall decrease in relative betweenness centrality among cheatgrass patches. Our results also showed a decrease in the relative closeness centrality for all but one cheatgrass patch, indicating that the network of greenstrips decreased the ability of fire to spread between patch pairs.

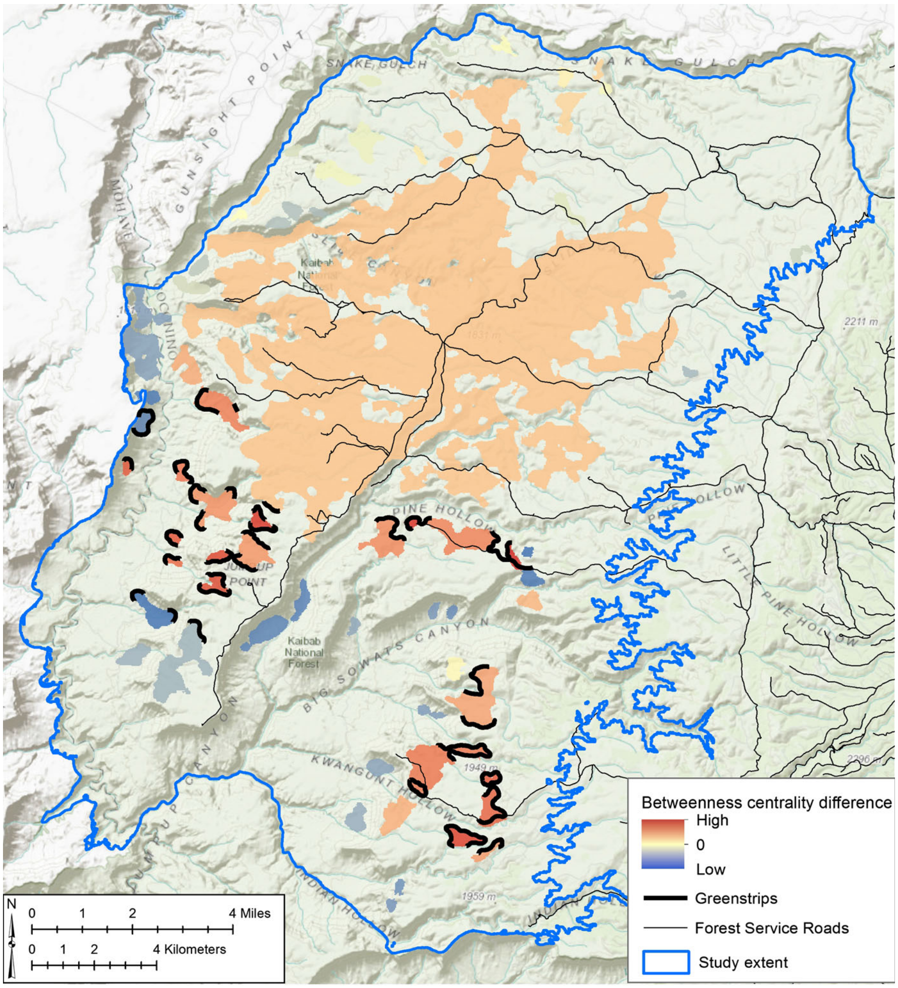

Fig. 7 Cheatgrass patches and associated differences in relative area-weighted betweenness centrality across the west side of the Kaibab Plateau. Differences were taken between the pre- and post-treatment scenarios of the depicted greenstrip network

While the results presented here show the potential for mitigation planning in our study area, the real promise of our approach lies in generating multiple management alternatives and facilitating decisions in light of costs, benefits, and other management objectives. This would greatly improve upon traditionally more ad hoc approaches to place greenstrips across a cheatgrass-invaded landscape (Pellant 1992). A few such decision support models have been applied in forested ecosystems (e.g., Parisien et al. 2007; Wei et al. 2008; Ager et al. 2013). For example, the Landscape Treatment Designer is a model for stand-level fuel treatments, and works with initial fire behavior thresholds and budget constraints to optimize the outcome of multiple treatments (Ager et al. 2013). The aggregate of treated and untreated stands aims to create a more fire-resilient landscape over time. This model deals with stand-level fuel treatments, but a similar optimization logic could easily be applied to our connectivity models for locating fuelbreaks. The process would be begin by setting management objectives and budget constraints, and follow with iterative application of the connectivity model to produce an optimized outcome of post-treatment centrality metrics. This approach would also be complementary to a broader fuels management strategy that integrates stand-level treatments (Agee et al. 2000). Another decision support model for the placement of fuelbreaks has been applied in Canadian boreal forests, and is premised on reducing the overall burn probability across a landscape (Parisien et al. 2007). The model takes into account the baseline burn probability as well as landscape

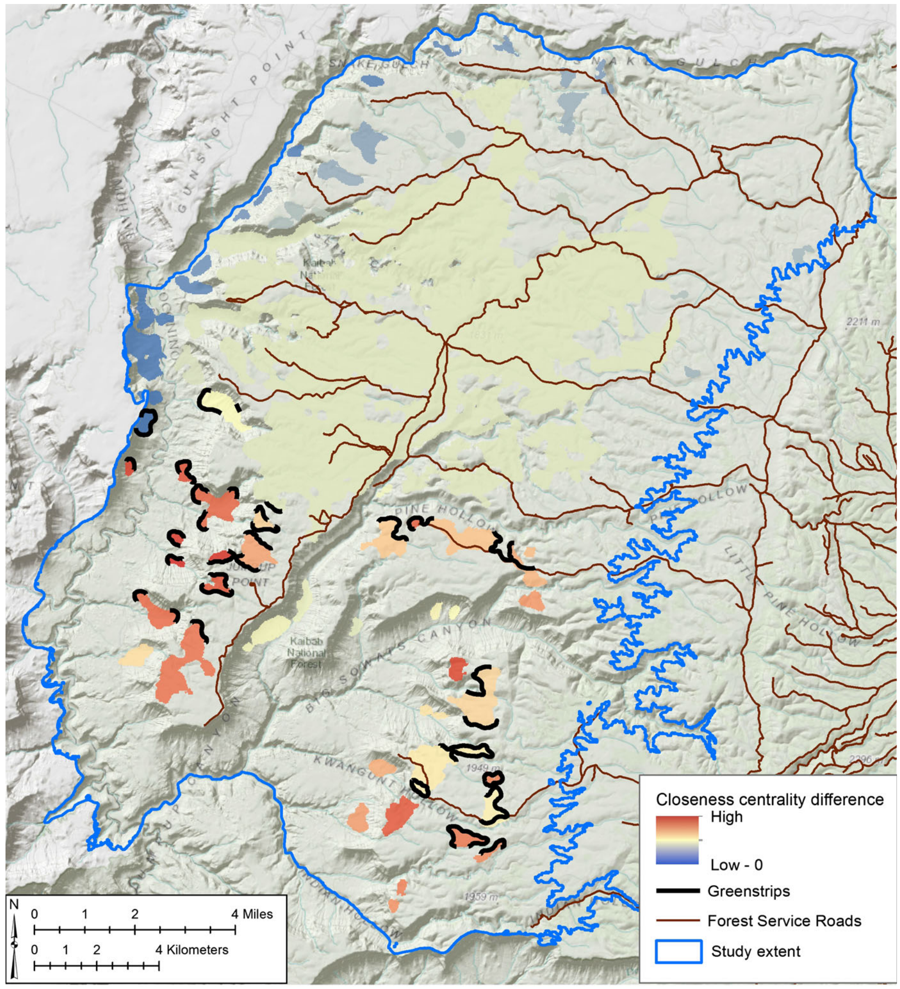

Fig. 8 Cheatgrass patches and associated differences in relative closeness centrality across the west side of the Kaibab Plateau. Differences were taken between the pre- and post-treatment scenarios of the depicted greenstrip network

features to prioritize fuelbreak placement, but lacks concise decision parameters to optimize landscape-level treatments.

The extension of our methods is also well suited for landscape fuels management in forested communities, for instance to mitigate where land-use and climate patterns have contributed to increases in large, severe wildfires (Westerling et al. 2006; Miller et al. 2008). In a connectivity model, the highest risk "patches" on the landscape would be those areas where large fires have a high likelihood of igniting and also facilitating the spread of fire in the larger landscape network. From a fire behavior perspective, fuel treatment placement can take into account the highest likelihood spread pathways around these patches and also the potential for unwanted fire behavior or effects. The flexible integration of fire connectivity models into landscape-scale vegetation and fire management can facilitate coordinated, science-based actions on-the-ground. Such efforts will be necessary to mitigate the negative, fire-related impacts that face landscapes globally.

Conclusion

Centrality metrics have played an important role in exposing focal points of flow for many ecological processes, primarily for the purpose of restoring connectivity across fragmented landscapes. In the context of fire and invasive plant management, our results are the first to show how they may also be used to keep a fragmented and heterogeneous landscape intact. Betweenness centrality metrics drew attention to focal areas on the landscape that would maintain high fire connectivity across a cheatgrass-invaded landscape. Subsequently, we evaluated the effectiveness of a potential greenstrip network by modeling the change in both betweenness and closeness centrality of those focal areas. The novel application of these metrics revealed the potential for diminished invasion/fire risk across the landscape, by focusing conservative mitigation action only around focal cheatgrass patches. With the ability to model fire connectivity across large landscapes, we see a great opening for centrality metrics to expose high-risk areas that can guide ecologically and economically efficient landscape fuels management.

Acknowledgments We thank the Arizona Game and Fish Department, the Grand Canyon Trust, and Wilburforce Foundation for funding this project. We thank S. Rosenstock with the Arizona Game and Fish Department and M. Williamson with the Grand Canyon Trust for valuable input that improved our approach, as well as C. Albano with the Grand Canyon Trust for the implementation of field sampling efforts. We also wish to thank V. Horncastle and the Lab of Landscape Ecology and Conservation Biology at Northern Arizona University for mapping and other support in the development of this work.

References

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

Agee JK, Bahro B, Finney MA, Omi PN, Sapsis DB, Skinner CN, Van Wagtendonk JW, Weatherspoon CP (2000) The use of shaded fuelbreaks in landscape fire management. For Ecol Manag 127:55–66

Ager A, Vaillant N, McMahan A (2013) Restoration of fire in managed forests: a model to prioritize landscapes and analyze tradeoffs. Ecosphere 4:1–19. doi:10.1890/es13-00007.1

Ager AA, Vaillant NM, Finney MA (2011) Integrating fire behavior models and geospatial analysis for wildland fire risk assessment and fuel management planning. J Combust. doi:10.1155/2011/572452

Balch JK, Bradley BA, D'Antonio CM, Gómez-Dans J (2013) Introduced annual grass increases regional fire activity across the arid western USA (1980–2009). Glob Chang Biol 19:173–183

Bodin Ö, Saura S (2010) Ranking individual habitat patches as connectivity providers: integrating network analysis and patch removal experiments. Ecol Modell 221:2393–2405. doi:10.1016/j.ecolmodel.2010.06.017

Borgatti SP (2005) Centrality and network flow. Soc Networks 27:55–71

Bradley BA (2009) Regional analysis of the impacts of climate change on cheatgrass invasion shows potential risk and opportunity. Glob Chang Biol 15:196–208

Bradley BA, Mustard JF (2005) Identifying land cover variability distinct from land cover change: cheatgrass in the Great Basin. Remote Sens Environ 94:204–213. doi:10.1016/j.rse.2004.08.016

Brandes U, Fleischer D (2005) Centrality measures based on current flow. In: Proceedings of the 22nd symposium on theoretical aspects of computer science. Springer, Berlin, 533–544

Brooks ML, Chambers JC (2011) Fire and invasive plants special feature: resistance to invasion and resilience to fire in desert shrublands of North America. Rangel Ecol Manag 64:431–438

Brooks ML, D'Antonio CM, Richardson DM, Grace JB, Keeley JE, DiTomaso JM, Hobbs RJ, Pellant M, Pyke D (2004) Effects of invasive alien plants on fire regimes. Bioscience 54:677–688

Carroll C, McRae BH, Brookes A (2012) Use of linkage mapping and centrality analysis across habitat gradients to conserve connectivity of Gray Wolf populations in western North America. Conserv Biol 26:78–87

Clinton NE, Potter C, Crabtree B, Genovese V, Gross P, Gong P (2010) Remote sensing-based time-series analysis of cheatgrass (*Bromus tectorum* L.) phenology. J Environ Qual 39:955–963. doi:10.2134/jeq2009.0158

Collins BM, Stephens SL, Moghaddas JJ, Battles J (2010) Challenges and approaches in planning fuel treatments across fire-excluded forested landscapes. J For 108:24–31

Compagnoni A, Adler PB (2014) Warming, competition, and *Bromus tectorum* population growth across an elevation gradient. Ecosphere 5:1–34

D'Antonio CM, Vitousek PM (1992) Biological invasions by exotic grasses, the grass/fire cycle, and global change. Annu Rev Ecol Syst 23:63–87

Dickson BG, Roemer GW, McRae BH, Rundall JM (2013) Models of regional habitat quality and connectivity for Pumas (Puma concolor) in the southwestern United States. PLoS ONE 8:e81898. doi:10.1371/journal.pone.0081898

Finney MA (2002) Fire growth using minimum travel time methods. Can J For Res 32:1420–1424

Finney MA (2004) FARSITE: fire area simulator: model development and evaluation

Finney MA (2006) An overview of flammap fire modeling capabilities

Fulé PZ, Waltz AEM, Covington WW, Heinlein TA (2001) Measuring forest restoration effectiveness in reducing hazardous fuels. J For 99:24–29

Gray ME, Dickson BG (2015) A new model of landscape-scale fire connectivity applied to resource and fire management in the Sonoran Desert, USA. Ecol Appl 25:1099–1113. doi:10.1890/14-0367.1

Gray ME, Dickson BG, Zachmann LJ (2014) Modeling and mapping dynamic variability in large fire probability in the lower Sonoran Desert of southwestern Arizona. Int J Wildl Fire 23:1108–1118

Hijmans RJ, van Etten J (2012) Raster: Geographic analysis and modeling with raster data

Hosmer DW, Lemeshow S (2000) Applied logistic regression, 2nd edn. John Wiley and Sons, New York

McRae BH, Dickson BG, Keitt TH, Shah VB (2008) Using circuit theory to model connectivity in ecology, evolution, and conservation. Ecology 89:2712–2724

Miller JD, Safford HD, Crimmins M, Thode AE (2008) Quantitative evidence for increasing forest fire severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA. Ecosystems 12:16–32. doi:10.1007/s10021-008-9201-9

Moghaddas JJ, Collins BM, Menning K, Moghaddas EE, Stephens SL (2010) Fuel treatment effects on modeled landscape-level fire behavior in the northern Sierra Nevada. Can J For Res 40:1751–1765. doi:10.1139/X10-118

Newman MEJ (2005) A measure of betweenness centrality based on random walks. Soc Netw 27:39–54. doi:10.1016/j.socnet.2004.11.009

Parisien M-A, Junor DR, Kafka VG (2007) Comparing landscape-based decision rules for placement of fuel treatments in the boreal mixedwood of western Canada. Int J Wildl Fire 16:664. doi:10.1071/WF06060

Pausas JG, Keeley JE (2014) Abrupt climate-independent fire regime changes. Ecosystems 17:1109–1120. doi:10.1007/s10021-014-9773-5

Pellant M (1989) The cheatgrass-wildfire cycle-are there any solutions? Symposium on cheatgrass invasion, shrub die-off, and other aspects of shrub biology and management, 11–18

Pellant M (1992) History and applications of the intermountain greenstripping program. Symposium on ecology, management, and restoration of intermountain annual rangelands. Boise, ID

Pontius RG, Parmentier B (2014) Recommendations for using the relative operating characteristic (ROC). Landsc Ecol 29:367–382. doi:10.1007/s10980-013-9984-8

R Development Core Team (2011) R: A language and environment for statistical computing

Scott JH, Burgan RE (2005) Standard fire behavior fuel models: a comprehensive set for use with Rothermel' s surface fire spread model

Sing T, Sander O, Beerenwinkel N, Lengauer T (2005) ROCR: visualizing classifier performance in R. Bioinformatics 21:3940–3941

Sisk TD, Albano C, Aumack E, Bernstein EJ, Crews TE, Dickson BG, Fluck S, McMaster M, Rogers AS, Rosenstock SS, Schlosberg D (2010) Integrating restoration and conservation objectives at the landscape scale: The Kane and Two Mile Ranch project. The Colorado Plateau IV: Shaping Conservation Through Science and Management. University of Arizona Press, Tucson, AZ, p 347

Stratton RD (2006) Guidance on spatial wildland fire analysis: models, tools, and techniques. Gen. Tech. Rep. RMRS-GTR-183. Fort Collins, CO

Theobald DM, Reed SE, Fields K, Soulé M (2012) Connecting natural landscapes using a landscape permeability model to prioritize conservation activities in the United States. Conserv Lett 5:123–133. doi:10.1111/j.1755-263X.2011.00218.x

Wei Y, Rideout D, Kirsch A (2008) An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. Can J For Res 38:868–877. doi:10.1139/X07-162

Westerling AL, Hidalgo HG, Cayan DR, Swetnam TW (2006) Warming and earlier spring increase Western US forest wildfire activity. Science 313:940–944

Whisenant SG (1989) Changing fire frequencies on Idaho's Snake River Plains: Ecological and management implications. In: McArthur, Romney EM, Smith SD, Tueller PT (eds) Symposium on Cheatgrass Invasion, Shrub Die-Off, and Other Aspects of Shrub Biology and Management. Ogden, UT, 4–10