FINAL REPORT

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For the project entitled:

Models and maps of pronghorn habitat quality and connectivity to inform 4FRI monitoring and vegetation treatment in Northern Arizona

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Introduction

Habitat loss due to changes in land-use patterns and climate has caused species decline and population fragmentation worldwide (Fahrig 2003). Maintaining connected habitats by conserving and restoring linkage zones or corridors has become one of the most common strategies for mitigating human-caused landscape changes (Heller and Zavaleta 2009). Therefore, conservation efforts are needed to identify where movement pathways may exist among populations. The decline in habitable area has been pervasive among North American ungulate species such as pronghorn antelope (*Antilocapra americana*), which has lost 64% of its historic range (Laliberte and Ripple 2004). Unfortunately, detailed knowledge of high quality habitat and areas that facilitate movement is particularly lacking for pronghorn in the US Southwest, including in north-central Arizona.

Ongoing vegetation treatments currently taking place as part of the Four-Forest Restoration Initiative (4FRI) in Arizona offer a unique opportunity to benefit pronghorn in addition to improving forest health and reducing fire risk. In collaboration with the Arizona Game and Fish Department (AZGFD), the 4FRI Multi-party Monitoring Board funded this modeling and mapping project that capitalizes on GPS collar data to help identify where forest treatments would best benefit pronghorn habitat and movement corridors.

Methods

Study area

The study area was defined as the extent bounded roughly by the Grand Canyon to the north, Prescott, AZ to the south, Ash Fork, AZ to the west, and Winslow, AZ to the east (Figure 1).

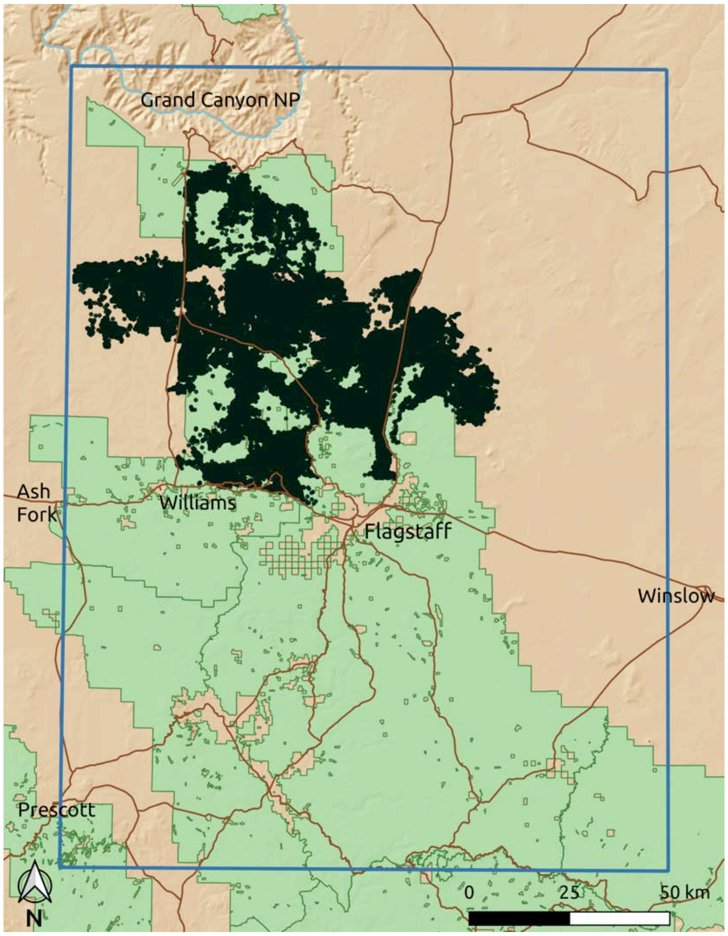

Figure 1. The study area is outlined in blue. Points in black are individual telemetry locations. Green represents National Forests and major roadways are brown.

Telemetry data

We received telemetry data for 87 pronghorn recorded by GPS collars deployed by the AZGFD, as well as information on the sex of each individual and deployment and retrieval data for each collar. Locations were recorded every 2 hours during daylight between October 2014 and December 2017. We cleaned the telemetry data by removing locations recorded prior to and two days following actual deployment, and after collar retrieval. We also removed records for the same individual at the same point in time and containing duplicate location and other collar data. The data generally spanned west to east across the study area, north of Interstate 40, and south of the Grand Canyon (Figure 1).

State-space model

We used a state-space modeling procedure to predict if each individual pronghorn was foraging or traveling at the time of each telemetry record. This type of model, also called a hidden markov model, is based on the assumption that there is an underlying, unobservable behavioral state which gives rise to the patterns evident in location data (Langrock et al. 2012). It employs a statistical technique to predict probability distributions for step length and turning angle between consecutive telemetry locations for each of a set number of behavioral states. These distributions can be used to determine the most likely behavioral state at the time of each telemetry record. As this type of model requires telemetry locations to be equally spaced in time, we added records for each individual for all overnight hours (during which the telemetry collars were not recording location data). These records were added at two-hour intervals to match the spacing of the rest of the data, and with unknown location. We specified that the state-space model estimated parameters for a gamma probability distribution for step lengths and a von Mises distribution for the turning angles. We set initial parameters of these distributions for each of the two behavioral states by using the telemetry locations of two individuals that we judged, upon examination in a GIS, to exhibit periods of extensive and seasonally-driven traveling behavior (IDs 8500 and 8502). For these two individuals, we defined point locations in the months of May through December to be periods of greater travel, and those in the other months to exhibit greater foraging behavior. These values were simply used to "seed" the models with reasonable initial values for model parameters. All models in this project were estimated on all individuals of both sexes. We used the *fitdistrplus* R package (version 1.0-9) to calculate summary statistics based on the corresponding probability distribution for points in each of these two time periods. We used the *moveHMM* R package (version 1.6) to estimate the state-space model.

Step-selection models

We used a step-selection model based on mixed conditional logistic regression to determine the relative preference by pronghorn for different environmental conditions in each predicted behavioral state. This type of model is based on a comparison of the actual ("used") telemetry locations to other locations ("available") on the landscape (Thurfjell et al. 2014). We used the probability distributions estimated by the state-space model to randomly select specific locations available for each individual "step" (travel between consecutive telemetry records) for all telemetry data. We created ten random locations for each actual location. We calculated separate sets of models for each behavioral state, in order to determine which environmental factors most influenced pronghorn movement, and whether that influence differed between states.

To parameterize the step-selection model, we first collected GIS data representing landscape properties and conditions that we hypothesized would most strongly influence movement by pronghorn. We based the selection of these factors on a literature review, discussion with project partners, and our own knowledge of the species and study area based on prior work (Fleishman et al. 2017). In order to meet project goals, we focused particularly on factors which would be most affected by forest treatment, such as amount of tree cover. All factors were considered to be possibly important to both traveling and foraging behavior. To represent land cover type and vegetation density, we collected Landfire existing vegetation type (EVT), height (EVH), and percent cover (EVC; v1.4.0; 30-m resolution; landfire.gov), and MODIS MOD44B vegetation continuous fields (VCF; 250-m resolution; lpdaac.usgs.gov/products/mod44bv006). EVT was re-classified into classes representing barren, developed, grassland, high elevation grassland, ponderosa pine / pine-oak, shrubland and pinyon-juniper. The landfire data was the most recent version available, and represented 2014 conditions. MODIS VCF included data through 2015. We collected topographic variables including elevation and slope from the Shuttle Radar Topography Mission (30-m resolution), and multiscale topographic position index (mTPI, used as a continuous data layer and not reclassified into multiple categories) and topographic diversity, both at 30-m resolution (Theobald et al. 2015). All raster data layers were obtained using Google Earth Engine. We also collected vector-based information on fire history, forest and range treatments, and barriers on the landscape, including USFS fire history, activity, and fence data for the Coconino and Kaibab National Forests and treatment locations on the Babbitt Ranches. In order to increase interpretability of regression coefficients and optimize model fit, we rescaled each continuous variable to a mean of zero and a standard deviation of one and recorded each categorical variable or class as a 1/0 "dummy" variable (Gelman and Hill 2006). We recorded the value of each of these variables at each telemetry location. Where values of a particular variable were constant within a specific point set (of one used and ten available locations) we added a small amount of random error to one random point. This ensured the step-selection models could be fit, and did not appear to appreciably alter results.

In cases where multiple GIS data layers were highly correlated or represented the same type of information, such as mTPI and slope, we estimated model parameters with each of the similar variables as a single predictor. We selected the variable contained in the model with the lowest value for Akaike's Information Criterion (AIC) for exclusive use in further models (Anderson 2008). In other cases, we excluded certain predictors because they did not cover the full extent of the study area, or did not contain enough relevant information to be useful in modeling. These excluded predictors included fire history, forest and range treatments, and barriers on the landscape. We created a suite of candidate models based on different hypotheses on the primary drivers of pronghorn habitat use and foraging. We used AIC to compete these models and selected the model with the lowest AIC value and for each behavioral state as the "best". This type of model does not contain an interpretable intercept coefficient, so we estimated a model with a random predictor to represent a "null", or uninformative, model. We used the *clogit* function in the *survival* R package (version 2.41-3) to create models with the corresponding predictors for each individual and determined the overall AIC value across all individuals as the average of the model (Burnham and Anderson 2002, Karelus et al. 2019). After using AIC values to determine the best models for each of the behavioral states, we estimated the final models using the *Ts.estim* function in the *TwoStepClogit* R package (version 1.2.5). To account for individual-level variation in preference, we parameterized these models with a fixed effect and a random coefficient for each predictor, grouped by each individual.

We used the step-selection model results for foraging and traveling states to create 30-m resolution maps that represented habitat quality and landscape resistance to movement, respectively. To do so, we used the inverse logit equation (Gelman and Hill 2006):

$$\frac{e^{\beta \mathrm{X}}}{1+\ e^{\beta \mathrm{X}}}$$

Here, β is the vector of regression coefficients from the corresponding model and X is the matrix of data values, in our case, the images representing the predictor variables. The result of this procedure is a map of habitat quality or landscape resistance across the study area, ranging from zero to one. We multiplied the landscape resistance map by 999 and added one to scale it to a theoretic range of 1-1000, in order to optimize it for use in Circuitscape.

Connectivity models

We used Circuitscape software (v4.0.5; circuitscape.org) to estimate pronghorn habitat connectivity using the resistance model and habitat quality models described above. Circuitscape uses aspects of circuit theory to represent a landscape as an electronic circuit board, with population areas serving as nodes connected across a landscape represented as a grid of resistors (McRae et al. 2008), thus estimating the relative likelihood of movement (or current flow) across an entire landscape and often revealing many possible pathways of movement. We used an omnidirectional connectivity model to predict potential connectivity across the landscape without regard to the location of specific core population areas (Pelletier et al. 2014). To derive this model, we created two pairs of parallel nodes (one image pixel wide) that extended across the east and west and north and south borders of the study area, respectively. We then used Circuitscape to calculate current flow by simulating the injection of one ampere of current into the node on one side and grounding the node on the other side. We used the landscape resistance map described above to represent resistance to movement by pronghorn. Once completed for each pair of nodes, the two models were added together to produce a wall-to-wall map of potential current flow across the study area.

To define corridors, we first used the habitat quality map to create a set of 1000 random points throughout the study area, weighted by habitat quality values. The weighting ensured that points were more likely to be placed in higher quality habitat. We created 500 pairs of random points and used a least-cost path analysis to draw the shortest path (in terms of resistance cost) between each pair.

Results

Telemetry data

The processed telemetry data contained approximately 397,000 telemetry locations for 87 individuals, ranging in time from October, 2014 to December, 2017.

State-space models

The results of the state space model are summarized in Table 1, and the probability distribution represented by these results is shown in Figure 2. The model estimated approximately 128,000 (33%) of all telemetry records were in time periods when pronghorn were in the “traveling” state and approximately 260,000 (67%) were when they were in the “foraging” state.

Table 1. Results for the state-space model.

Behavioral State	**Step length (gamma distribution)**		**Turning angle (Von mises distribution)**	
	Mean distance (m)	*Standard deviation*	*Mean*	*Concentration*
Traveling	984.40	820.16	-0.0214	-0.594
Foraging	375.86	390.75	0.645	0.0141

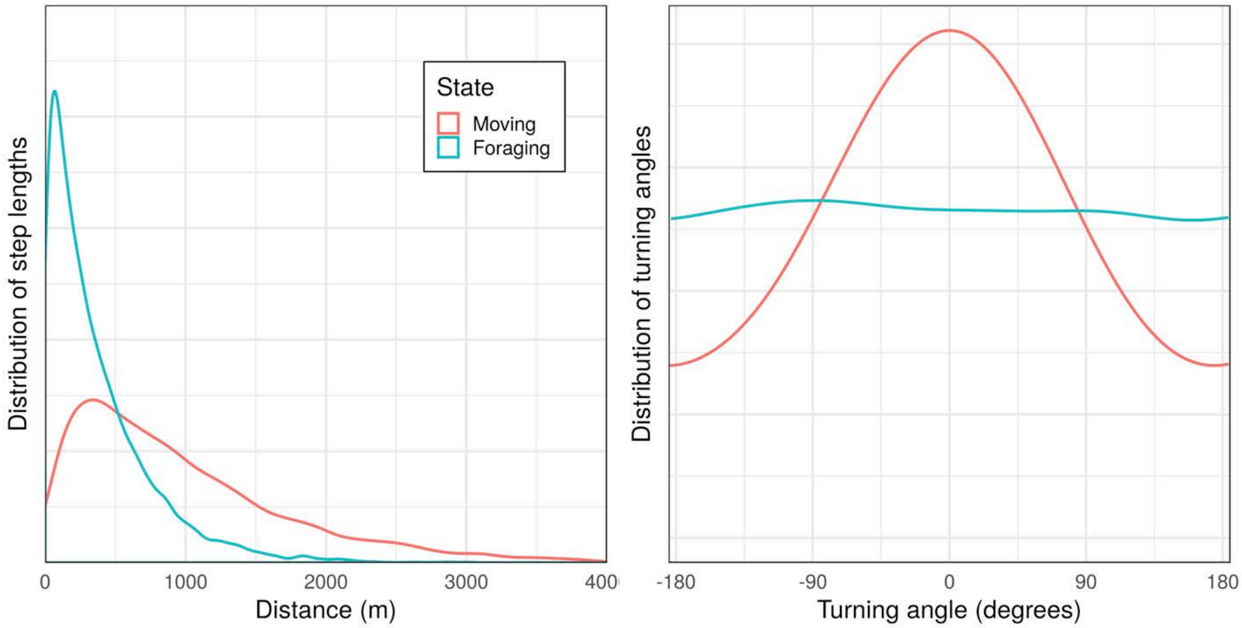

Figure 2. The probability distributions estimated by the state-space model for each of the behavioral states.

Step-selection models

We fit single variable step-selection models to determine which variables containing different representations of the same landscape attributes best represented the data. In particular, we competed models with slope, mTPI, and topographic diversity and EVC and MODIS-derived percent cover. Topographic diversity and EVC performed best in both traveling and foraging states and were used in further modeling (Table 2).

Table 2. Step-selection model results for traveling and foraging behavioral states.

Predictors	**AIC (traveling)**	**ΔAIC (traveling)**	**AIC (foraging)**	**ΔAIC (foraging)**
% Herb cover + % Shrub cover + % Tree cover + Developed + Grassland + PineOak + PJ + Shrubland + Topo diversity	7192.40	0.00	14194.10	0.00
% Herb cover + % Shrub cover + % Tree cover + Developed + Grassland + Other + PineOak + PJ + Shrubland + Topo diversity	7194.22	1.82	14197.08	2.98
% Herb cover + % Shrub cover + % Tree cover + Topo diversity	7194.54	2.15	14208.78	14.68
% Herb cover + % Shrub cover + % Tree cover + Barren + Developed + Grassland + HighGrassland + PineOak + PJ + Shrubland + Topo diversity	7194.98	2.58	14197.05	2.96
% Herb cover + % Shrub cover + % Tree cover	7195.66	3.27	14220.96	26.86
% Tree cover	7197.91	5.51	14236.71	42.61
Barren + Developed + Grassland + PineOak + PJ + Shrubland	7203.15	10.76	14241.43	47.33
MODIS % tree cover	7208.16	15.76	14236.20	42.10
Topographic diversity	7223.58	31.19	14277.57	83.48
mTPI	7227.48	35.09	14289.44	95.34
Slope	7228.75	36.35	14291.28	97.19
Null model (random predictor)	7231.76	39.36	14303.75	109.65

We estimated a suite of models for each behavioral state using the remaining predictors and based on several hypotheses about their likely effects on pronghorn movement. In particular, we parameterized a model based solely on land cover type, on the hypothesis that pronghorn are only affected by the dominant type; a model based solely on vegetation cover, based on the hypothesis that they only respond to the quantity of vegetation; a model with cover variables plus topographic position, suggesting they respond to the quantity of vegetation as well as topography; and three models which considered cover variables as well as various land cover classifications (Table 2). In both the moving and foraging states, the model which performed best included percent tree cover, percent shrub cover, percent herbaceous cover, topographic diversity, and developed, grassland, pine-oak, pinyon-juniper, and shrubland land cover classes. The parameter estimates for these model results for both moving and foraging states are shown in Table 3. We used these results to create the habitat quality and landscape resistance maps (Figure 3). The omnidirectional connectivity map, also containing 500 least-cost pathways estimated between using pairs of random points is shown in Figure 4.

Table 3. Model results for the best model (judged by lowest AIC value) for both the foraging and traveling states, with the corresponding beta values, stand errors, and 95% confidence intervals for each predictor and in each state. A positive beta value indicates pronghorn are more likely to move into areas with higher values of the corresponding predictor (or presence of that land cover type), and a negative value indicates they are less likely.

Predictor	**Foraging state**			**Moving state**		
	Beta	*SE*	*95% CI*	*Beta*	*SE*	*95% CI*
% Herb cover	0.012	0.007	(-0.0017,0.026)	0.0072	0.0059	(-0.0043,0.019)
% Shrub cover	0.084	0.014	(0.057,0.11)	0.026	0.013	(0.00019,0.051)
% Tree cover	-0.16	0.023	(-0.2,-0.11)	-0.18	0.017	(-0.21,-0.14)
Developed	-0.038	0.0083	(-0.054,-0.022)	-0.0084	0.011	(-0.029,0.012)
Grassland	0.068	0.015	(0.04,0.096)	0.084	0.016	(0.053,0.11)
PineOak	0.034	0.011	(0.012,0.056)	0.03	0.012	(0.0075,0.053)
PJ	-0.05	0.012	(-0.073,-0.027)	-0.08	0.014	(-0.11,-0.053)
Shrubland	0.096	0.016	(0.064,0.13)	0.092	0.018	(0.057,0.13)
Topo diversity	-0.13	0.093	(-0.31,0.049)	-0.33	0.051	(-0.43,-0.23)

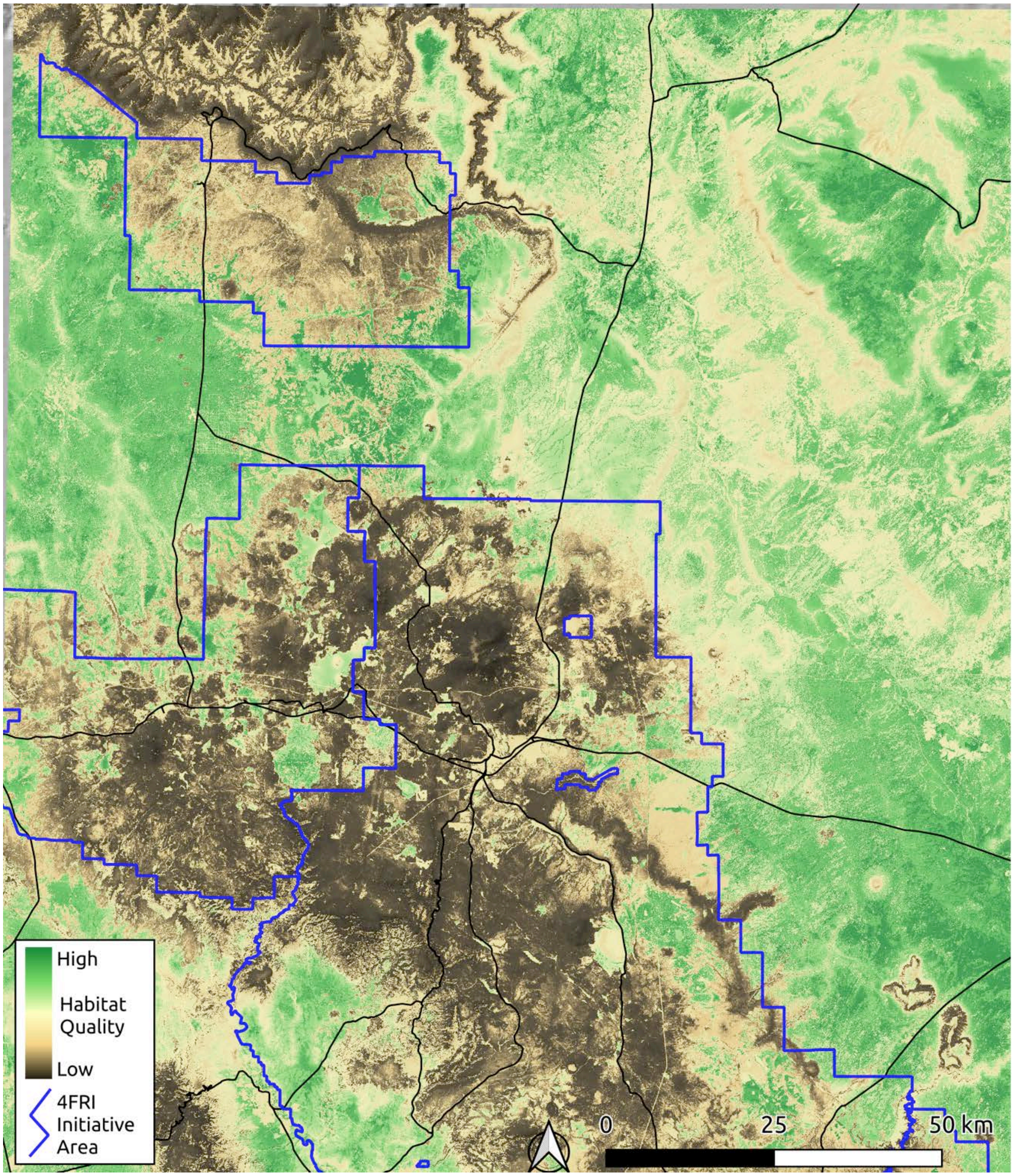

Figure 3. Map of habitat quality for pronghorn. Brown indicates low relative quality, green indicates high.

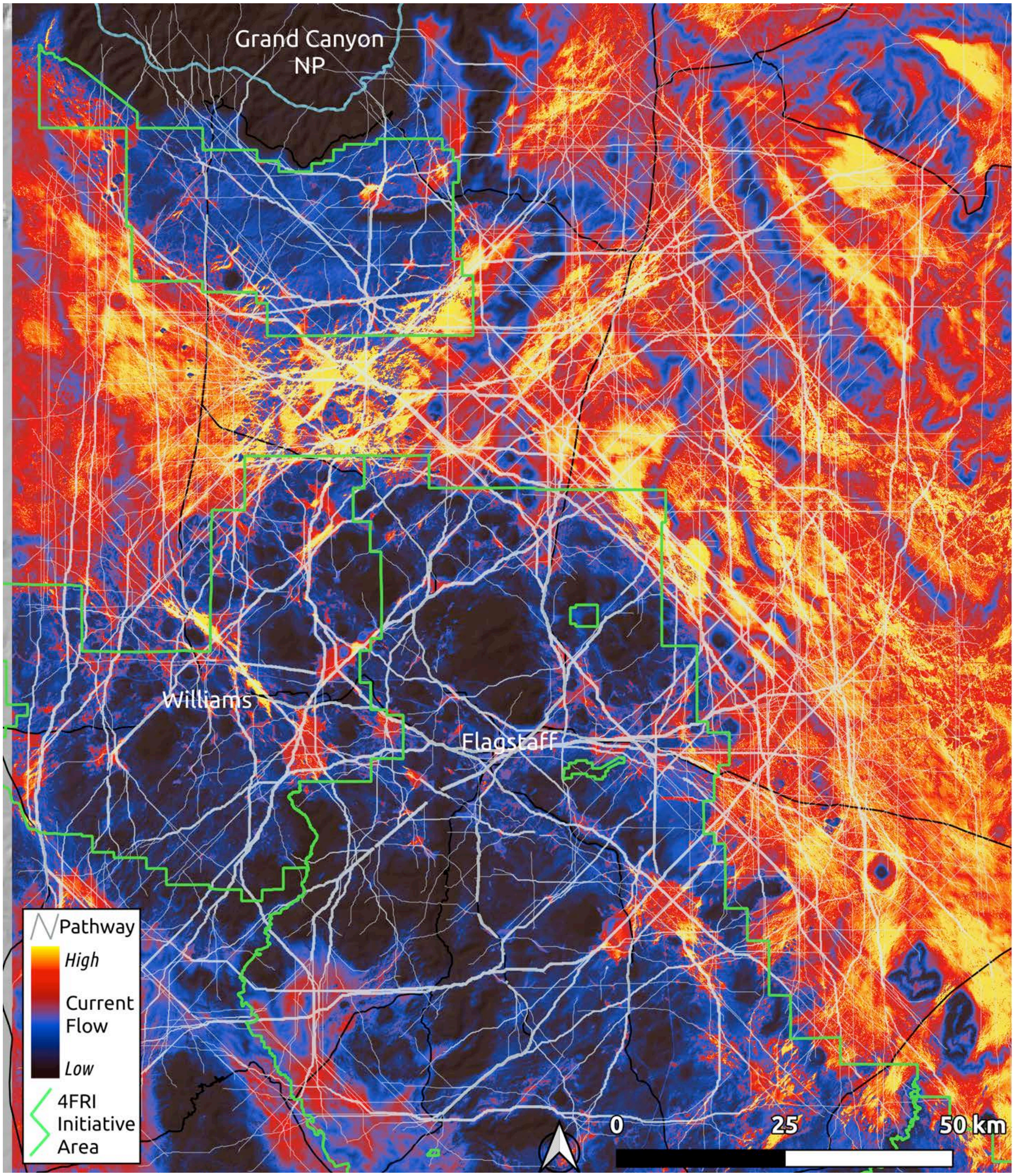

Figure 4. Omnidirectional connectivity (black to yellow) and least cost pathways (white) between random points for pronghorn in northern Arizona. Greater numbers of overlapping pathways (represented by thicker white lines) indicate important corridors, which, in places of low current flow may indicate where movement is most impeded.

Discussion

State-space modeling results showed differences in distribution of step length and turning angle in each of the two predicted behavioral states. Average step lengths were much greater in the traveling state, and directional persistence much stronger. These patterns indicate the state-space model captured periods of greater movement as well as more settled periods.

Step-selection results for both traveling and foraging states indicate that pronghorn respond to a variety of cues on the landscape, as better-performing models tended to be those which accounted for a greater number of predictors and predictor types. In each state, percent tree cover and topographic diversity tended to be the strongest predictors of movement, indicating that individuals tended to move through flatter areas with lower tree cover. Results also suggest that pronghorn respond similarly to different land cover classes in each state, preferring shrubland and grassland areas most strongly, and avoiding pinyon-juniper and developed areas. While results suggest individuals prefer areas with slightly higher shrub and herbaceous cover in both states, this affinity is stronger in the foraging state, which may be related to forage quantity.

The map of habitat quality depicts highest quality pronghorn habitat in the east, southwest, and central portions of the study area. This reflects the results of the step-selection model for the foraging state, which predicts greater quality habitat in land cover classes and areas with fewer trees and flatter topography. To a certain extent, the map of omnidirectional connectivity shows patterns of movement that mimic the underlying habitat quality. This is somewhat logical given the similarity in models results between the two behavioral states. However, it also shows amplified current flow ("pinch-points") among several islands of high quality habitat such as near Government prairie, on Anderson mesa, and among mixed grassland/shrubland and pinyon-juniper woodlands north of the San Francisco Peaks. These patterns are also evident in the map of least-cost pathways. These results suggest that areas that are most constrictive of pronghorn movement are those showing low current flow along overlapping least-cost pathways (Figure 4). Our recommendation is that forest treatments that reduce percent tree cover would be best placed in areas such as these.

For this project, we did not expressly simulate or evaluate the size of treatment areas or the width of corridors that would most benefit pronghorn. One rule-of-thumb which has been suggested is that corridors should be 2-km wide (Beier 2019). It is our opinion that such a size would indeed confer benefits to pronghorn movement. Based on examination of the telemetry data, corridors already being used could possibly be an order of magnitude smaller. Indeed, ultimately there appear to be few environments on the landscape to which pronghorn do not travel, except perhaps areas of extreme elevation and topography (such as the Grand Canyon and the top of the San Francisco Peaks) or across strong barriers such as highways and certain fences. This suggests that while vegetation type may restrict movement, the likely benefits of treatments may be stronger for forage quality and quantity. Additionally, we did not evaluate the likely impacts on pronghorn movement of different treatment intensities, such as reducing tree cover by or to a certain percent. However, modeling results showed greater avoidance of pinyon-juniper than pine-oak land cover types, which indicates near-ground visibility may also be a factor in movement preference. Finally, as topographic diversity was the strongest predictor of landscape use in the model for the traveling state, and the strongest predictor overall, treatments in areas of high topographic diversity may have less benefit to pronghorn than similar treatments on flat areas.

Treatment effects on habitat quality and connectivity could be evaluated in the future by obtaining or creating up-to-date maps that accurately depicts the effects of treatments on vegetation cover and type. These layers would likely be limited to those representing land cover type and vegetation percent cover. The habitat quality, permeability, and connectivity models could be re-created with these modified layers using the same parameters from the step-selection models and the same connectivity modeling procedure. The new output layers could be compared to the results of this analysis to show the impacts of treatments both within and around their perimeter. In a future situation where the GIS data layers used in this analysis have not been updated, or do not accurately capture treatment effects, knowledge on the extent and intensity of forest treatments could be used to "burn-in" treatments on existing maps. Conversely, if other information sources are found which do capture such information, this analysis could be repeated with those layers at both past and present conditions.

Due to analytical limitations, some data which was collected for this project was not leveraged when estimating step-selection models. In some cases this was due to the footprint of such data, which may have been limited solely to the extent of national forests, or just portions of them. Models and analyses could be re-run for a limited area if interest in including these layers exists. In some cases, this information was incomplete in extent but also lacking in quality. For instance, while fence data were collected for portions of the study area, examination of the data in a GIS indicated that fences were often mis-aligned with those that could be perceived on aerial photos. Additionally, there was no way to evaluate the size and status of a given fence, and whether it would prove to be a barrier to pronghorn movement. Nevertheless, high quality information on barriers would likely prove to be an important predictor in studies such as this.

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