

The Answer is Blowing in the Wind:
Modeling the Impacts of Wind Turbine
Installations on Western Burrowing Owl
Habitat in West Texas

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Introduction and Problem Statement

With more than 30 gigawatts of installed capacity, Texas leads the US in wind energy production, which provides over 17% of the electricity consumed within the state (EIA). Because Texas contains a substantial amount of the land suitable for future wind energy installations, it will play an important role in efforts to decarbonize the electric grid ([EIA](#)). However, wind farms introduce their own set of environmental consequences, including temporary or permanent habitat disturbance, noise pollution, and increased bird and bat mortality rates due to collisions (Drewitt & Langston, 2006). As wind energy becomes an increasingly important form of electricity production, it is important to consider its impacts on biodiversity. Turbine siting decisions should maximize potential wind energy production while minimizing the loss of ecosystem services.

With the intent of eventually developing a model that will 1) optimize wind energy siting and 2) predict the environmental impacts of wind farms in west Texas, I am using a combination of GIS and the Natural Capital Project's [InVEST Habitat Quality model](#) to explore the impacts of existing wind farms in west Texas (Pecos, Upton, and Crockett counties) on western Burrowing Owl (*Athene cunicularia hypugaea*) habitat. In particular, I hope to understand whether the modeled impacts of wind turbines differ according to land cover type, wind farm density, or other factors.

Background

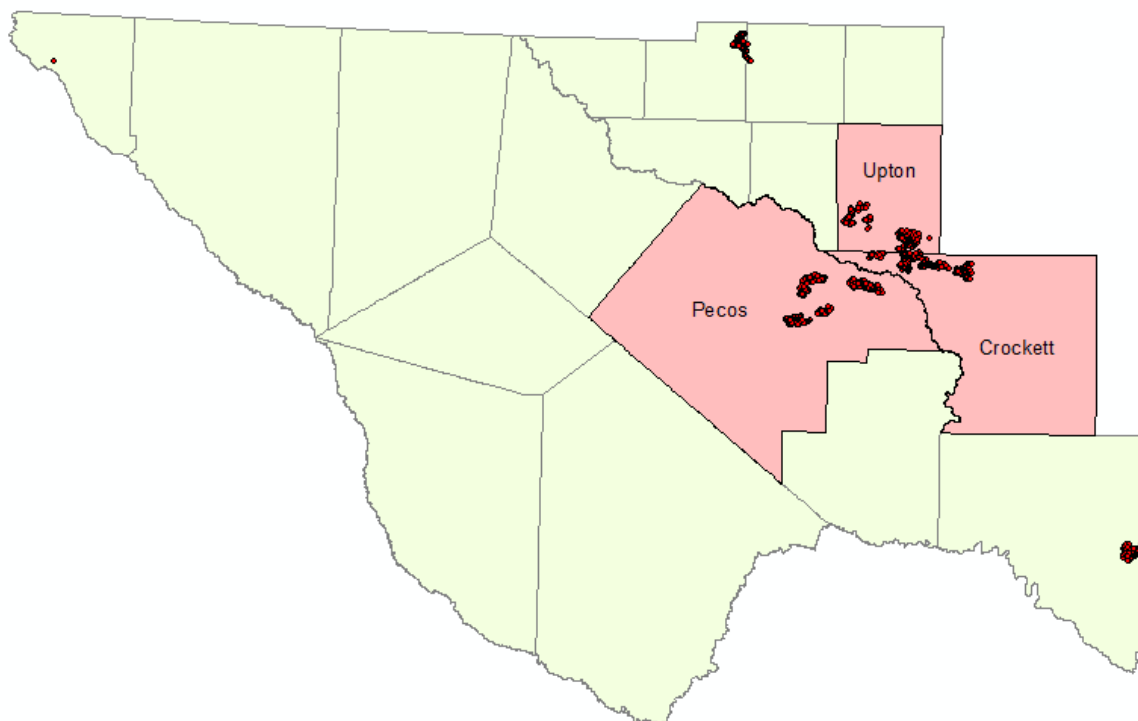
The risks that wind farms pose to bird species are well-documented, including collisions with wind turbines, direct land use change, habitat disturbance due to edge effects, noise, and light pollution, and altered migration pathways (Drewitt & Langston, 2006). However, many of these impacts are challenging to quantify, particularly because the quality of each risk varies depending on species characteristics (habitat preferences, seasonal and diurnal occupational patterns, flight height, flock size, life cycle stage). Most studies have a small temporal (a few years or seasons) and physical (single wind farm) scale. In particular, much of the literature that is regionally applicable to west Texas focuses on collision risks instead of broader habitat degradation issues (e.g. Wulff et al., 2016). Because west Texas is one of the most biodiverse regions both statewide and nationally, and because the region is targeted for substantial future wind development, it is important to understand and attempt to quantify the current and potential future impacts of wind farm installations on biodiversity and particularly avian species.

The Stanford University Natural Capital Project has developed a series of modeling tools for evaluating ecosystem services and the risks posed to them, including the [InVEST Habitat Quality model](#). This model has the ability to estimate the spatial impacts of multiple risk factors on habitat quality, based on land use rasters and information about the extent and relative effects

of risk factors on different habitat categories. The Habitat Quality model also has the capacity to estimate future impacts (if a future land use raster is provided), which makes it particularly useful in understanding both current and future risks to biodiversity and ecosystem services.

Because I do not have prior experience with the InVEST modeling tools or with quantifying the impacts of wind turbines on bird species, I chose to focus on a specific geographic area and species as a “test case,” with the goal of eventually scaling my results to a regional scale and across numerous bird species in iterations. Out of my 18-county region of interest in west Texas, I selected a tricounty area spanning Pecos, Upton, and Crockett Counties that includes the highest regional concentration of wind turbines (Figure 1). I selected the western Burrowing Owl (*Athene cunicularia hypugaea*) as my “test” species because much of the land across the tricounty study area qualifies as suitable habitat, and because prior studies indicate that the species is at risk of increased mortality and other negative impacts due to wind turbines (Smallwood et al., 2007). The western Burrowing Owl has a G4, S2 species rank, indicating that it is globally secure but rare or vulnerable within Texas; as such, there are multiple biodiversity and ecosystems services-related motivations for conserving the species within the study area (Klute et al., 2003).

Figure 1. The 18-county area of interest in west Texas, with currently operating wind turbine locations denoted by red markers. In this project, I am focusing on the three west Texas counties (colored pink) with the highest concentrations of wind turbines: Pecos, Upton, and Crockett.



Data Collection

The InVEST Habitat Quality model requires a set of two raster inputs: a current land use/land cover (LULC) raster, and raster(s) representing the threats of interest.

Land Use/Land Cover

I downloaded the United States Geological Survey (USGS) GAP Land Cover raster from ArcGIS online. This raster provides land cover data at a resolution of 30 m and is categorized by the National Vegetation Class (NVC) as well as a series of subclasses and macrohabitats.

Threat Raster

In this project, I am specifically interested in wind turbines as a threat to bird habitats; as such, current wind turbine sites constituted my sole threat raster. I obtained locations (latitude/longitude coordinates) for wind turbine sites from the USGS [Wind Turbine Database](#) and Federal Aviation Administration (FAA) [wind turbine location data](#) (downloaded in October 2020). I originally accessed this data in the form of zipped Excel files.

Miscellaneous Data

In order to define my study area and provide geographic context for my results, I retrieved Texas county outlines from the Texas Department of Transportation's open-access ArcGIS Online collection (TPP_GIS).

I wanted to compare my western Burrowing Owl habitat classifications to the USGS habitat model results. I downloaded a raster dataset (cell size = 30 m) representing modeled western Burrowing Owl habitat in the United States from the [Gap Analysis Project website](#).

Data Processing

Processing in ArcGIS

Because I intend to apply my project findings to a larger study area that encompasses west Texas, and because InVEST modeling requires a projection measured in meters, I selected the NAD83(2011) Texas Centric Albers Equal Area projection (unit is meters) for my analysis.

I used the selection tool in ArcGIS to select my three counties of interest (Pecos, Crockett, and Upton) from the Texas county outlines shapefile and exported the selection as a polygon feature class with the Texas Centric Albers projection. This tricounty region constitutes my study area for this project, which I used to mask all of my relevant datasets (Figure 1). I converted the datasets I collected to the Texas Centric Albers projection while I was clipping each layer, using the "Extract by Mask" tool ("Environments" → "Output Coordinates" → "As specified below") for raster datasets and the "Clip" tool for vector datasets (Table 1).

The USGS and FAA wind turbine datasets were originally in the form of Excel spreadsheets, so I had to convert the Excel data to a shapefile and then to a raster for use in the InVEST model (Table 1). I first added each spreadsheet to ArcMap, and then used the “display XY data” function to map the turbine locations via the latitude and longitude columns included in each spreadsheet. Although USGS and FAA turbine datasets largely overlapped, both sources included a few unique entries. I used the “Merge” tool to combine the two datasets into a single point feature class; this step also allowed me to project the resulting feature class into Texas Centric Albers (meters) through the “Output Coordinates” setting (Figure 4). I then used the “Point to Raster” tool to transform this feature class to a raster dataset with a resolution of 10 m, and reclassified the resulting raster to represent “turbine” vs. “nonturbine” locations (Figure 2; Figure 3; Figure 4).

Initial attempts at using the InVEST Habitat Quality Model with a higher-resolution LULC proved challenging due to large file sizes, so I resampled the GAP Land Cover raster from a 30 m to a 100 m resolution using the Resample tool and the Nearest Neighbors method (Figure 5; Table 1). I then reclassified this resampled Land Cover raster according to its NVC categorization in preparation for use in the InVEST model (Figure 6).

Table 1. A summary of the metadata and processes I used to create my study area and the raster dataset inputs for the InVEST Habitat Model.

Dataset	Description and Attribute(s) Used	Original Resolution/Extent	Date	Source	Processing
Tri-county Study Area	Polygon feature class containing Pecos, Upton, and Crockett County outlines. Used as a mask for other files, and to define the study area for this project.	Extent: Texas	2019	TXDoT (TPP_GIS library accessed via ArcGIS Online)	<ol style="list-style-type: none"> 1. Select three counties of interest, use “Create Layer from Selected Features” tool. 2. Export new layer as feature class (Texas Albers projection).
Land Use Land Cover (LULC) raster	100 m raster of US NVC data to characterize land use/land cover and western Burrowing Owl habitat. Used as an input for InVEST Habitat Quality model.	Cell size: 30 m Extent: US	2011 (data) 2019 (raster)	USGS Land Cover GAP (accessed via ArcGIS Online)	<ol style="list-style-type: none"> 1. Clip raster down to tricounty area (Texas Albers projection). 2. Resample raster to 100 m resolution using Nearest Neighbors method (tricounty mask). 3. Reclassify raster by NVC values.
Wind turbine raster	10 m raster denoting wind turbine locations. Used as an input (threat raster) for InVEST Habitat Quality model.	Extent: US	Current through 10/2020	USGS and FAA wind turbine databases (Zip files containing Excel spreadsheets)	<ol style="list-style-type: none"> 1. Import spreadsheets into ArcGIS; use “display XY data” on latitude/longitude columns. 2. Use “Merge” tool to combine USGS and FAA datasets into point feature class (Texas Albers projection). 3. Use “Point to Raster” tool to convert point features to a 10 m raster dataset (tricounty mask). 4. Reclassify wind turbine raster so that all cells have the same value.

Figure 2. Point-to-raster conversion of the wind turbine feature class, using a cell size of 10 m and tricity study area as a mask.

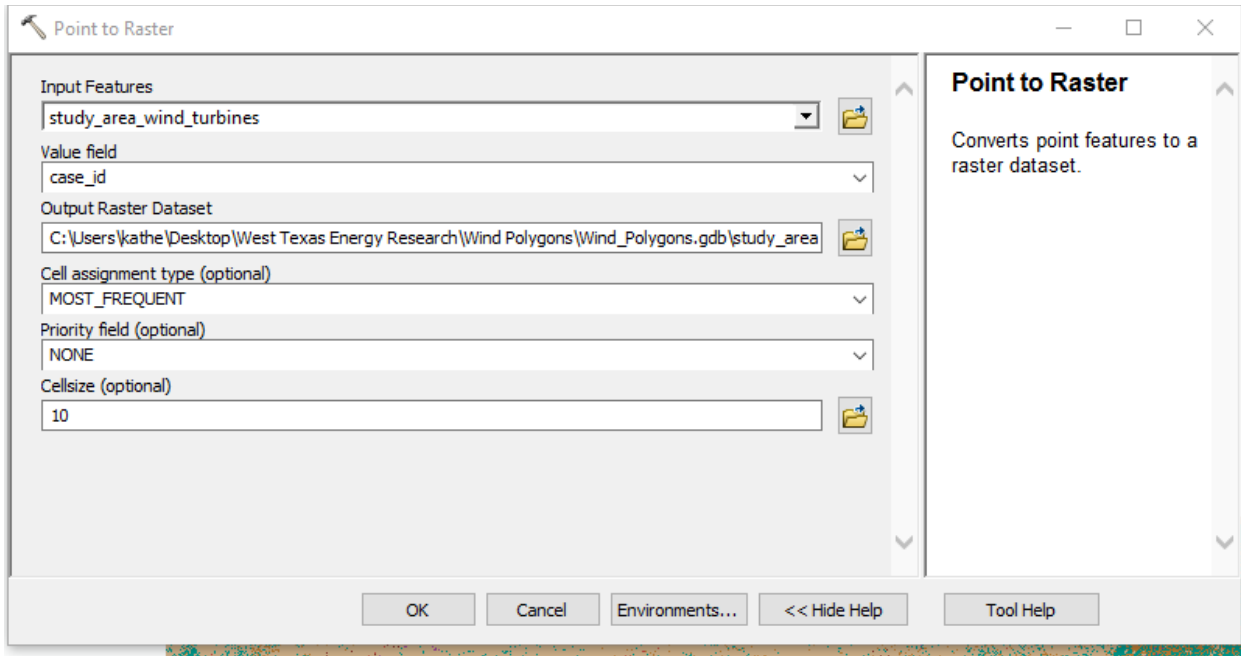


Figure 3. My initial wind turbine raster had values corresponding to turbine IDs, but the model only required binary functionality (turbine/not turbine). I reclassified the wind turbine raster so that all cells had a value of 1.

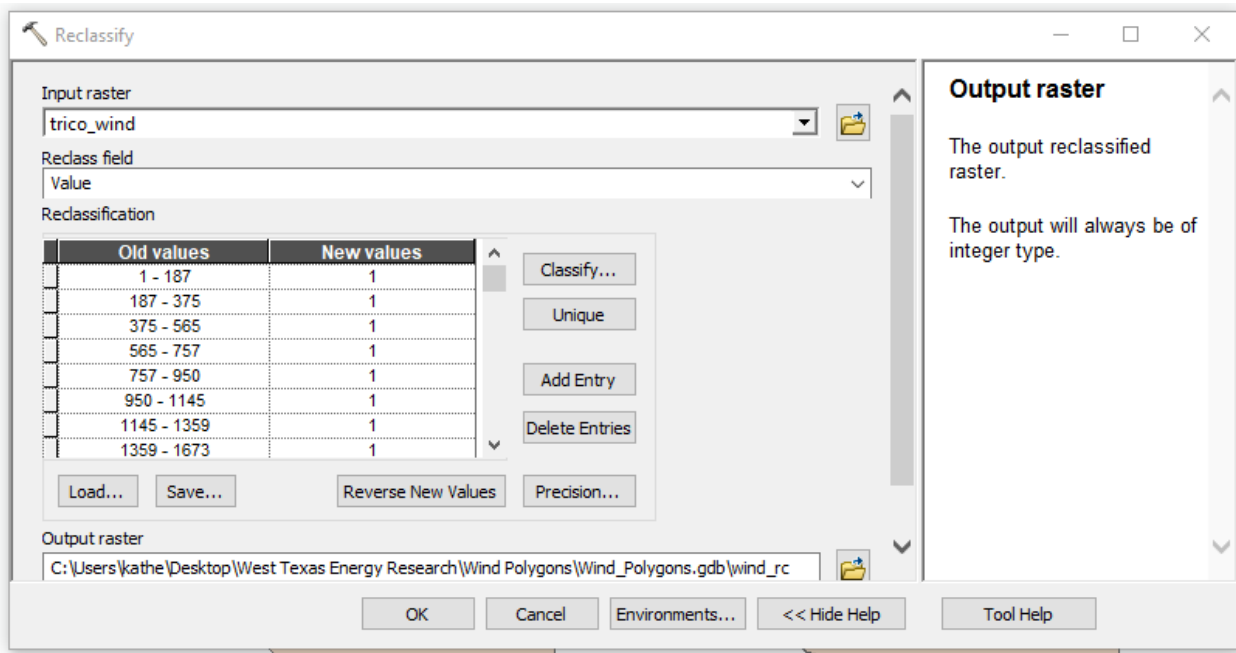


Figure 4. (Top) The wind turbines point feature class, with red markers denoting turbine locations. (Bottom) The wind turbines raster dataset, created using the “Point to Raster” tool in ArcGIS. Dark cells (size = 10 m) contain wind turbines.

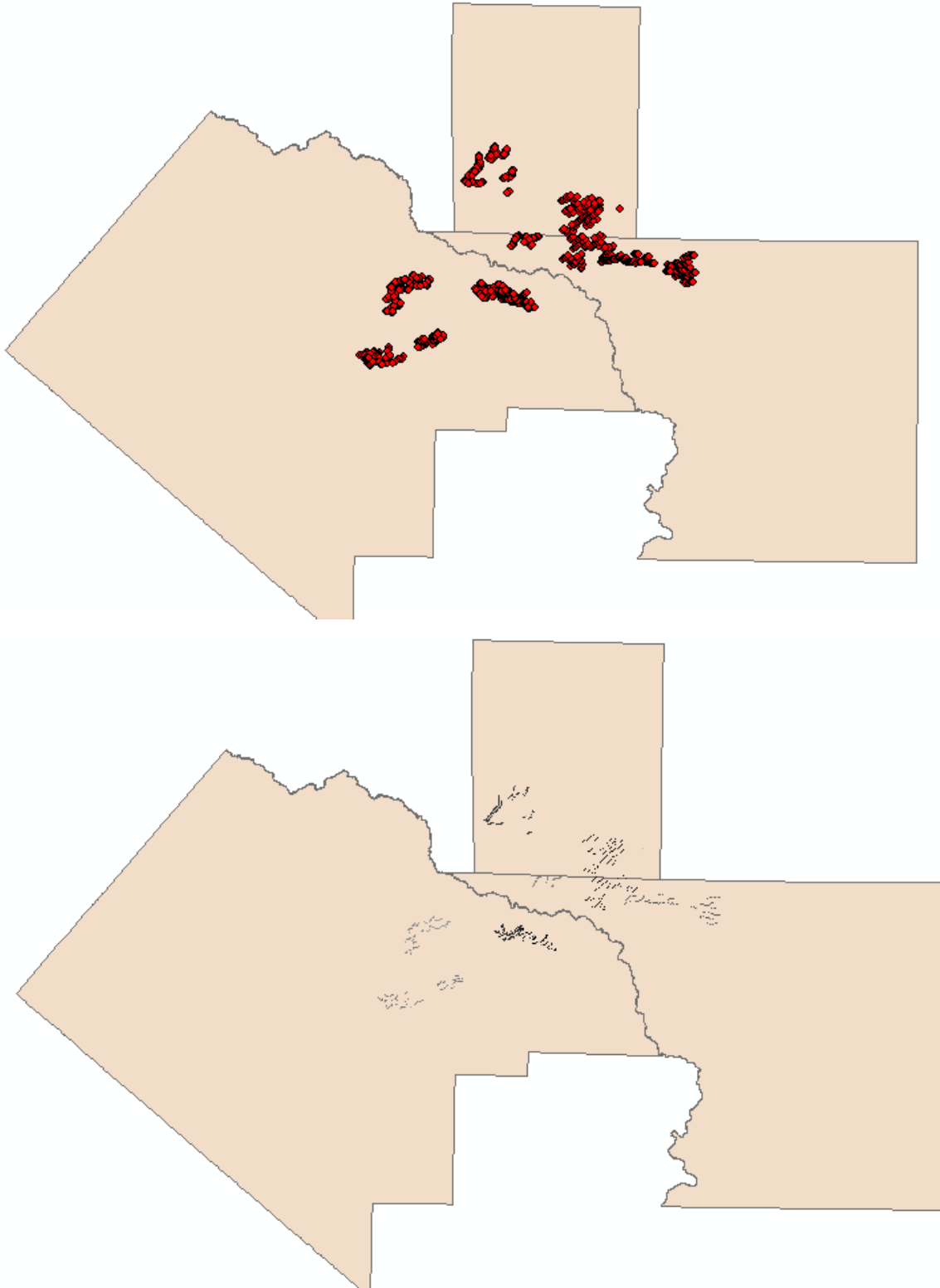


Figure 5. (Top) The original clipped national GAP analysis dataset, with a cell size of 30 m. (Bottom) I used the Resample tool and the “Nearest Neighbors” method to create a GAP raster with a cell size of 100 m (and applied the study area mask to the results).

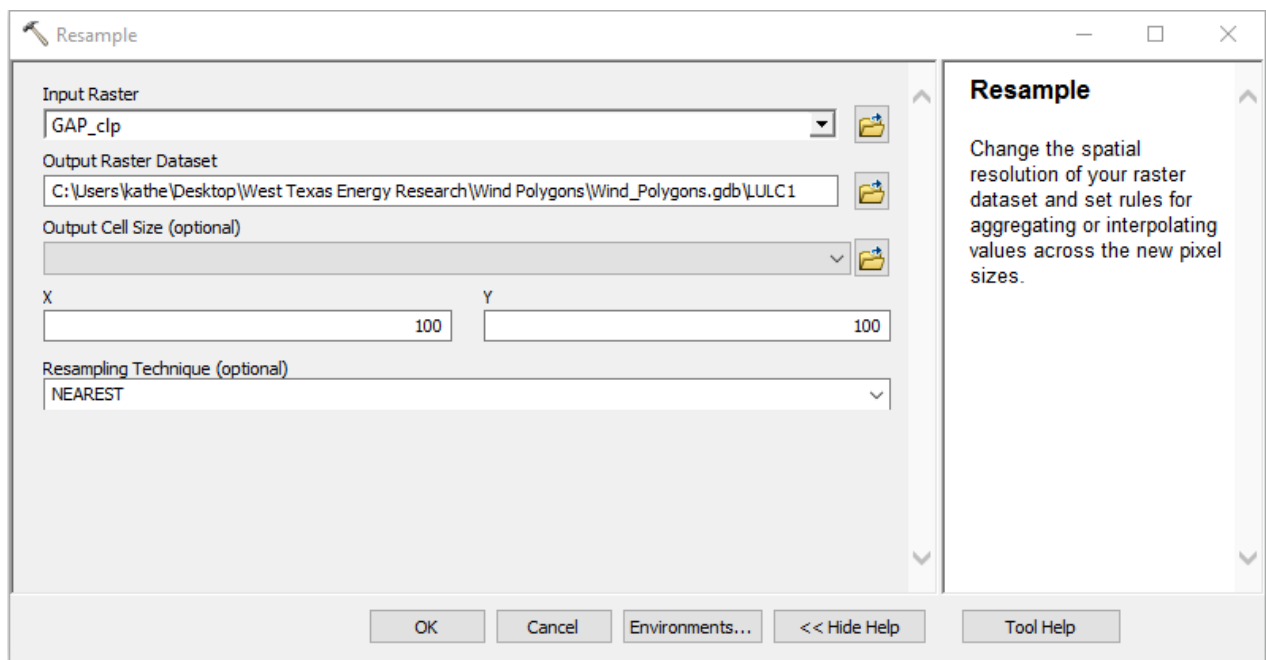
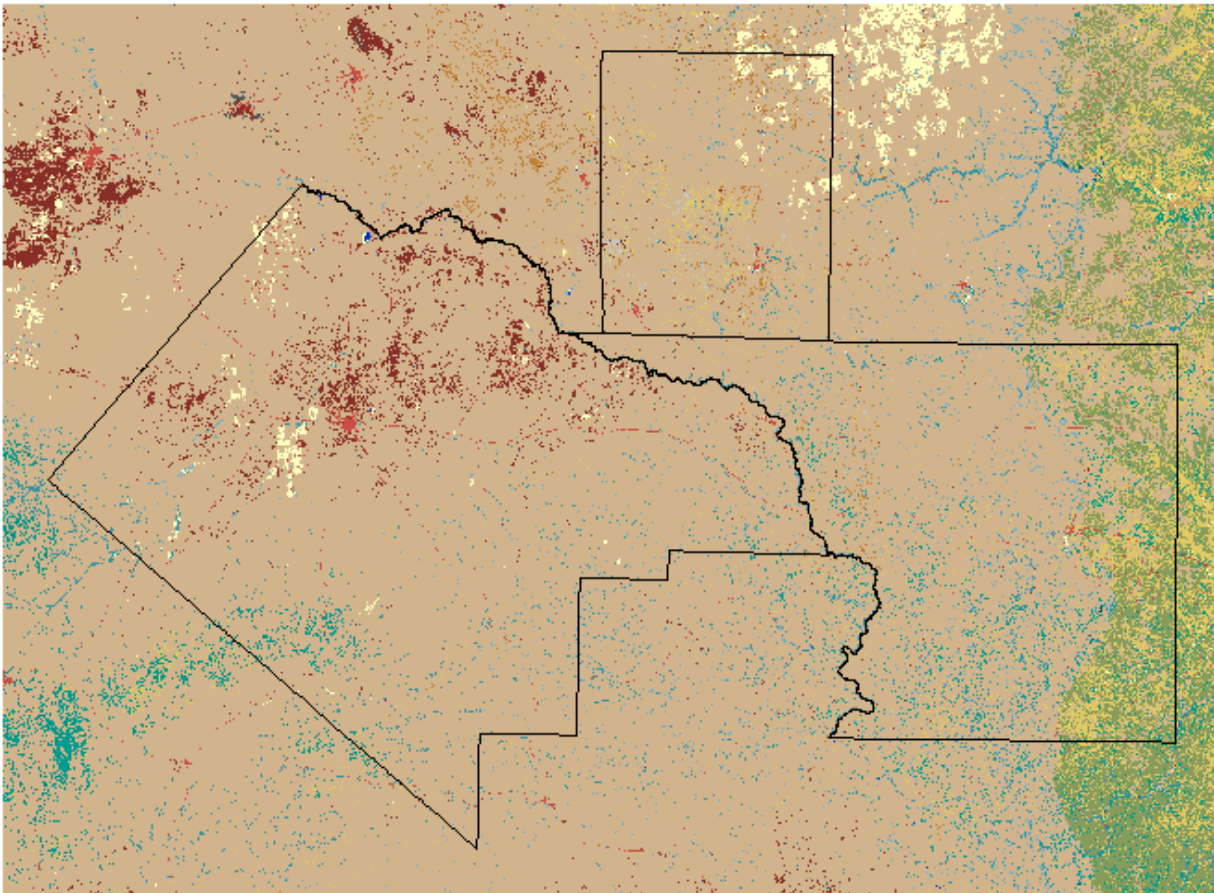
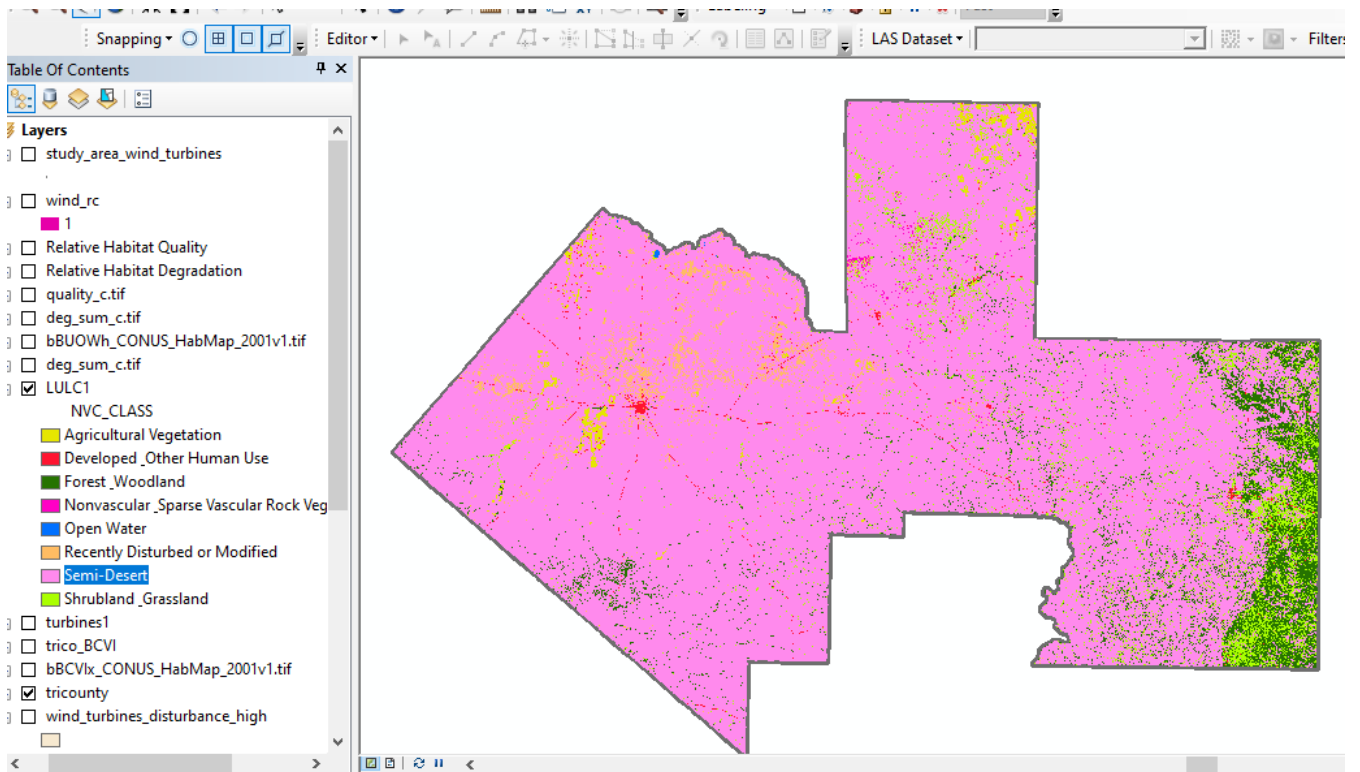
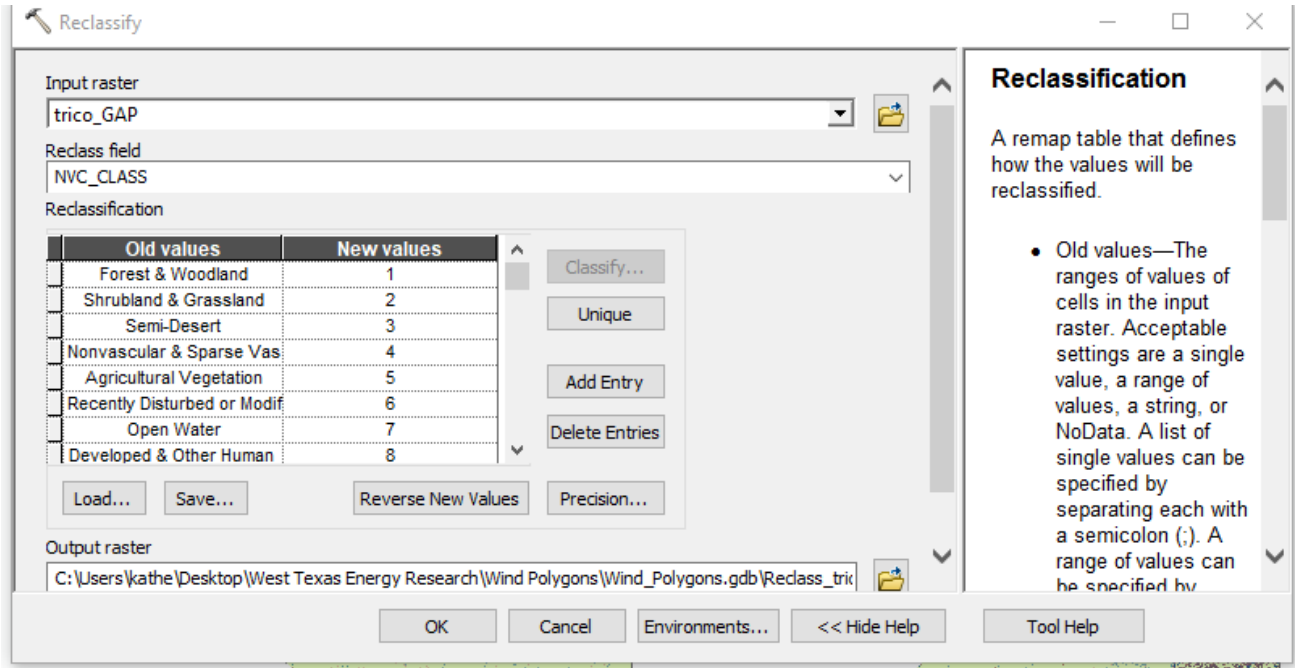


Figure 6. (Top) After resampling the GAP dataset to a 100 m resolution, I reclassified cells by their NVC categorization (values 1-8) and clipped the output raster to the tricounty study area. (Bottom) The reclassified Land Use/Land Cover raster. This raster dataset constituted my land user raster input for the InVEST Habitat Quality model.



InVEST Habitat Quality Modeling

The InVEST Habitat Quality model has five required inputs: a workspace folder (i.e. a designated location for model outputs), a current land cover raster, a csv file with threat data, a csv file with threat sensitivity data, and a half-saturation constant.

The threat csv file represents each relevant threat in a row that includes maximum impact distance, weight (floating point value between 0 and 1), type of decay over distance (linear or exponential), and the file path to the relevant raster file (Table 2). Studies of bird displacement due to wind farms estimate habitat disturbance radii extending 200-600 m from wind turbines (Drewitt & Langston, 2006). Based on these estimates, I chose a liberal maximum impact distance of 0.6 km (600 m) and assumed that the threats posed by wind turbines (collision risk, direct land disturbance, etc.) would decay exponentially with increasing distance.

Table 2. Threat csv file input for the Habitat Quality model. “MAX_DIST” is measured in kilometers, and weight is on a scale from 0 to 1.

THREAT	MAX_DIST	WEIGHT	DECAY	CUR_PATH
wind	0.6	1	exponential	C:\Users\kathe\Desktop\West Texas Energy Research\GIS Final Project\Threat Rasters\wind_c.tif

The threat sensitivity csv file corresponds to the land cover raster. Each value from the land cover raster is assigned an explanatory name, a habitat value, and a value for each relevant threat (in this case, wind turbines). Habitat values range from 0 to 1, where 0 represents non-habitat classes and 1 represents the most highly-preferred habitat (Table 3). In the case of the western Burrowing Owl, I used a combination of USFWS and USGS habitat description data to devise the following classifications for my NVC land cover data (Klute et al., 2003; Laxson & Rubino, 2017):

- Nonhabitat (value = 0): Forest & Woodland; Open water
- Adequate habitat (value = 0.5): Recently disturbed or modified; Developed & other human use
- “Above-adequate” habitat (value = 0.75): Agricultural vegetation
- Preferred habitat (value = 1): Shrubland & Grassland; Semi-desert; Nonvascular and sparse vascular vegetation

Threat values also range from 0 to 1. Non-habitat classes and classes that are impervious to the threat in question receive a value of 0, while land cover that is at maximum disturbance risk receives a value of up to 1. I determined wind turbine threat values using the land recovery estimates reported in Denholm et al. (2009). Desert habitat recovery times are estimated to

exceed one decade, so I assigned semi-desert and nonvascular/sparse vascular vegetation a wind threat value of 1. Grassland recovery times are estimated at 2-3 years, so I assigned shrubland/grassland and agricultural vegetation wind threat values of 0.3 and 0.5, respectively. Developed and modified lands are excluded from wind farm development, so those classes received values of 0 alongside other non-habitat land classes (Table 3).

Table 3. Threat sensitivity csv file input for the Habitat Quality model. LULC values correspond to land cover raster values, and habitat and wind values are on a scale from 0 to 1.

LULC	NAME	HABITAT	wind
1	Forest & Woodland	0	0
2	Shrubland & Grassland	1	0.3
3	Semi-desert	1	1
4	Nonvascular and sparse vascular vegetation	1	1
5	Agricultural vegetation	0.75	0.5
6	Recently disturbed or modified	0.5	0
7	Open water	0	0
8	Developed & other human use	0.5	0

After preparing my csv files and raster layers, I ran the Habitat Quality model, which (Figure 7). The model outputs two relevant rasters: “deg_sum_c,” which includes relative habitat degradation values based on threat inputs, and “quality_c,” which includes relative habitat quality values based on LULC and threat inputs (Figure 8). Both raster datasets assign values of 0 to cells that do not qualify as habitat.

Figure 7. The InVEST Habitat Quality model workspace from my second iteration of the western Burrowing Owl habitat model (adjusted half-saturation constant).

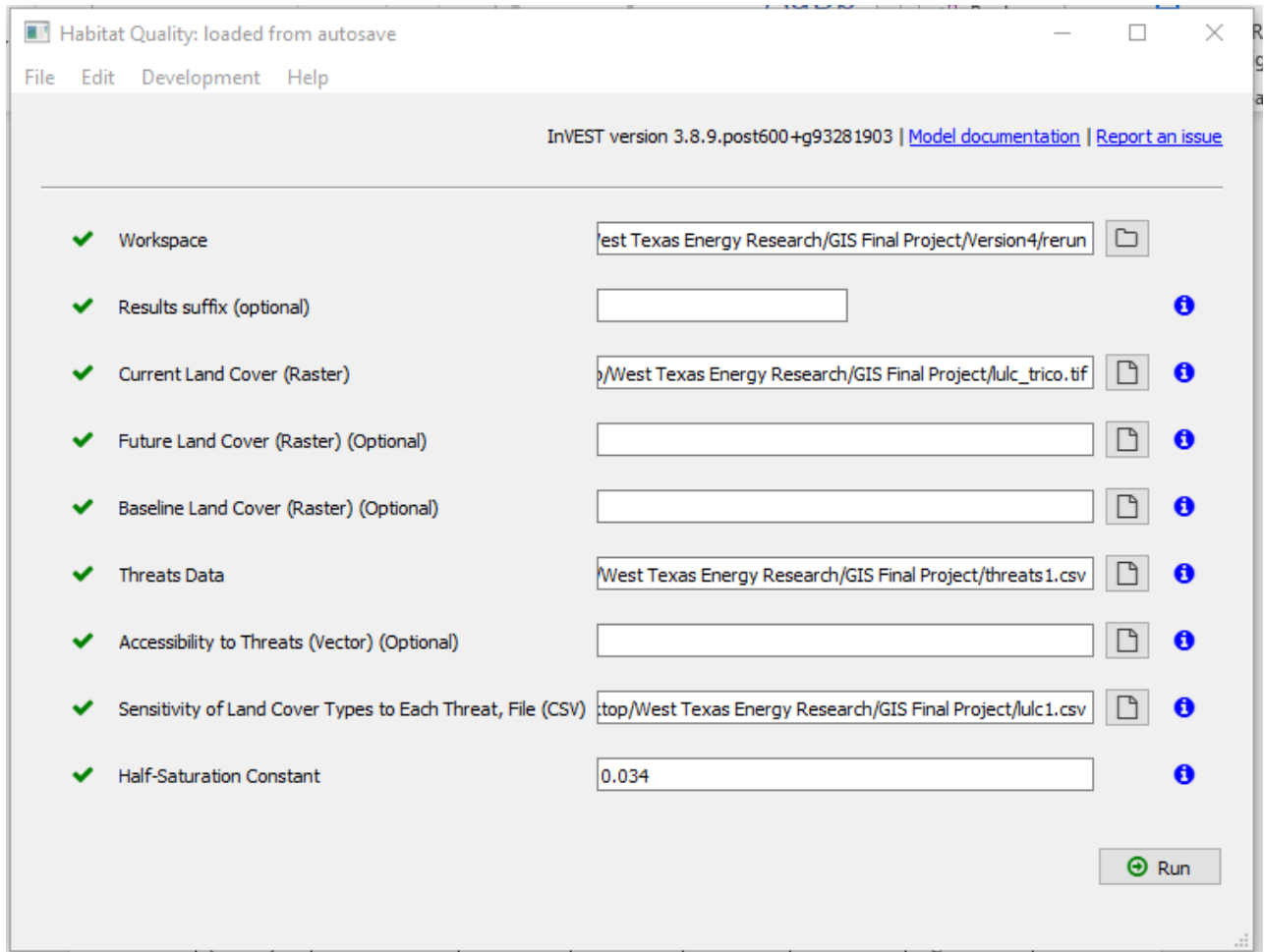


Figure 8. Files generated from one iteration of the InVEST Habitat Quality model. The most relevant outputs are the “deg_sum_c” and “quality_c” TIFF files, which are raster representations of relative habitat degradation and habitat quality, respectively.

GIS Final Project > Version4 > rerun				
Name	Date modified	Type	Size	
intermediate	12/6/2020 8:31 PM	File folder		
deg_sum_c	12/6/2020 8:32 PM	TIF File	889 KB	
deg_sum_c.tif.ovr	12/6/2020 8:32 PM	OVR File	212 KB	
InVEST-Habitat-Quality-log-2020-12-06--...	12/6/2020 8:31 PM	Text Document	7 KB	
quality_c	12/6/2020 8:32 PM	TIF File	905 KB	
quality_c.tif.ovr	12/6/2020 8:32 PM	OVR File	248 KB	

Results

The “relative habitat quality” and “relative habitat degradation” rasters generated by the InVEST Habitat Quality model contain *relative* values that lack units and intrinsic meaning. Higher cell values correspond to relatively high-quality habitat and relatively strongly-degraded habitat, respectively, while cell values of 0 indicate nonhabitat. In light of the relative-value nature of these datasets, I used the Jenks Natural Breaks method to classify the rasters into “low,” “medium,” and “high” quality/degradation categories (and 0 for nonhabitat/nondegraded cells). Figure 9 illustrates relative habitat quality results and Figure 10 illustrates relative habitat degradation results for the tricounty study area.

Relative habitat quality results make sense in light of threat sensitivity inputs (Table 3). Independent of wind turbines, cells that are classified as “disturbed” or “developed” land use correspond to relatively low habitat quality values, while “shrubland,” “semi-desert,” and “sparse vascular vegetation” cells have relatively high quality values (Figure 9). Similarly, it makes sense that relative habitat degradation values decrease with distance from wind turbine locations (Figure 10).

Densely-clustered wind turbine installations are associated with low habitat quality values and relatively high habitat degradation values, likely due to overlapping radii of influence (Figure 11; Figure 12). Interestingly, relatively sparsely-distributed wind turbines appeared to have a minimal impact on modeled habitat quality (Figure 11; Figure 12). In “sparser” wind turbine clusters, habitat degradation values remained relatively low and habitat quality values remained relatively high—to the point of falling under the “relatively high quality” habitat category generated through Jenks Natural Breaks classifications.

Figure 9. Habitat quality modeling results for the Western Burrowing Owl. Nonhabitat regions are shown in gray, relatively low-quality habitat is in red, moderate-quality habitat is in yellow, and relatively high-quality habitat is in green. Cell values are relative and lack intrinsic meaning.

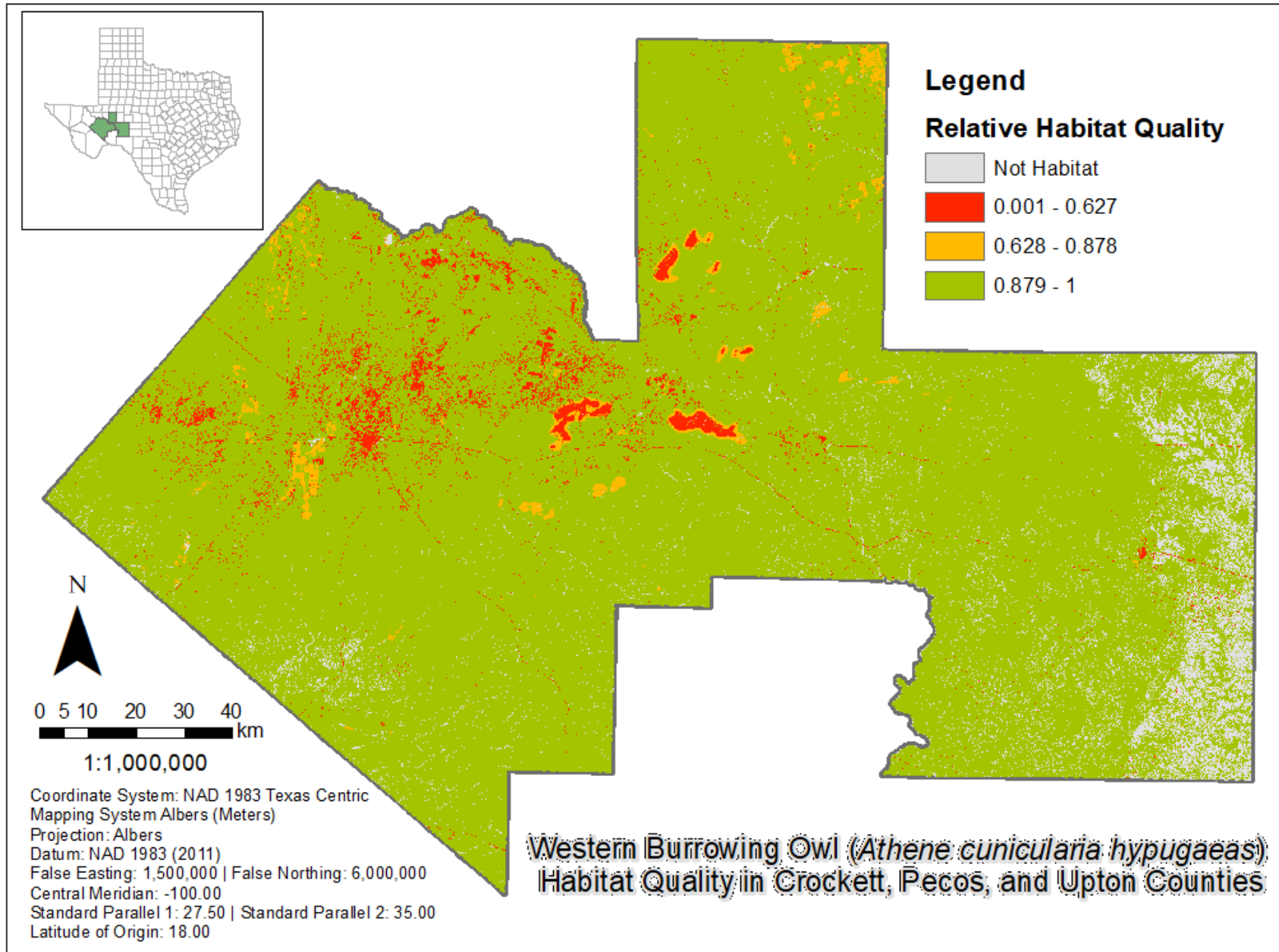


Figure 10. Habitat degradation modeling results for the Western Burrowing Owl, indicating regions of degradation associated with wind turbine installations. Nonhabitat or undisturbed regions are shown in gray, relatively undegraded habitat is in green, moderately-degraded habitat is in yellow, and relatively strongly-degraded habitat is in red. Cell values are relative and lack intrinsic meaning.

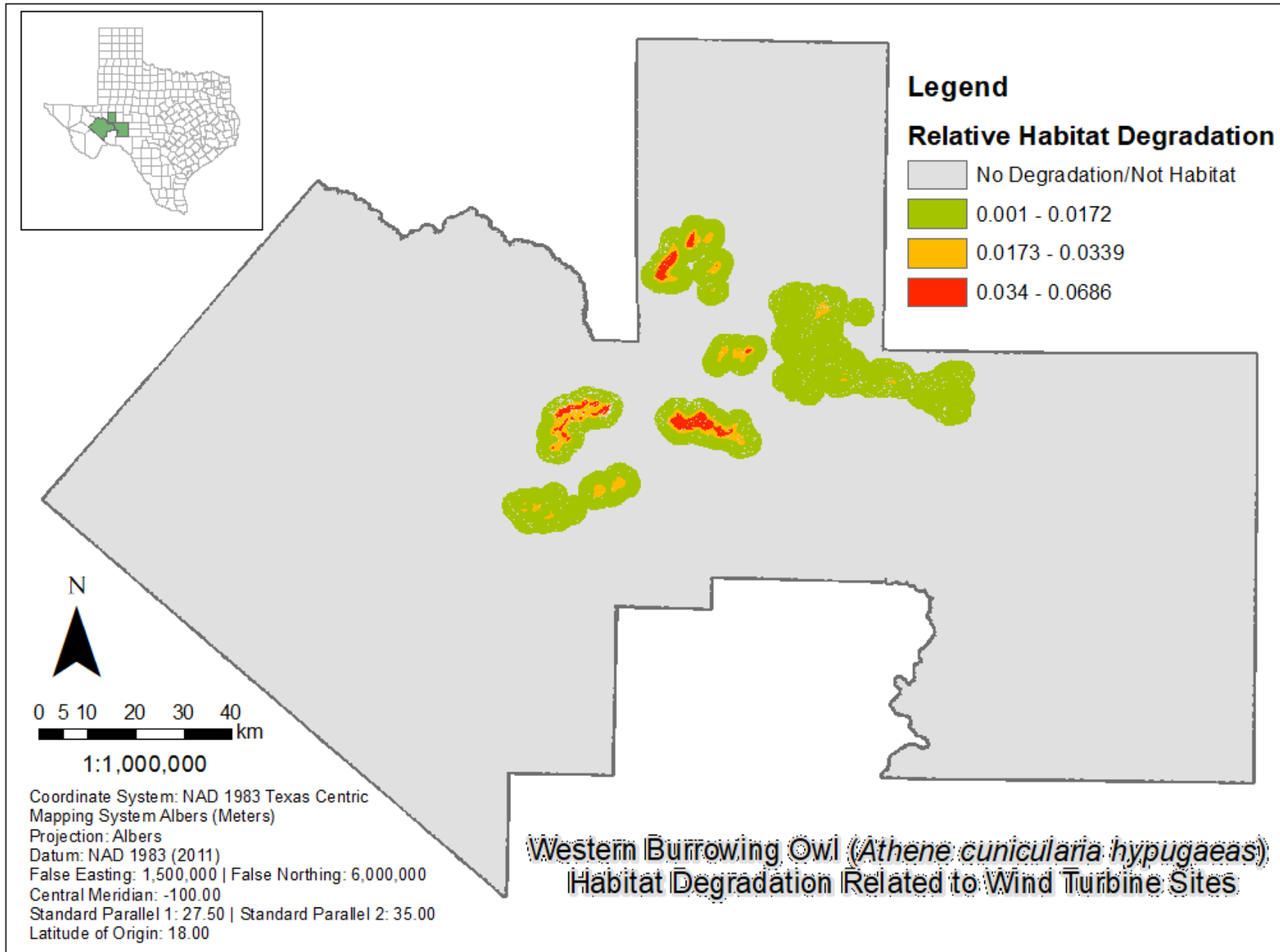


Figure 11. A magnified version of Figure 9, showing relative habitat quality results and wind turbine locations. While densely clustered wind turbines correlate with lower habitat quality values, other wind turbine strings appear not to be associated with significant reductions in habitat quality.

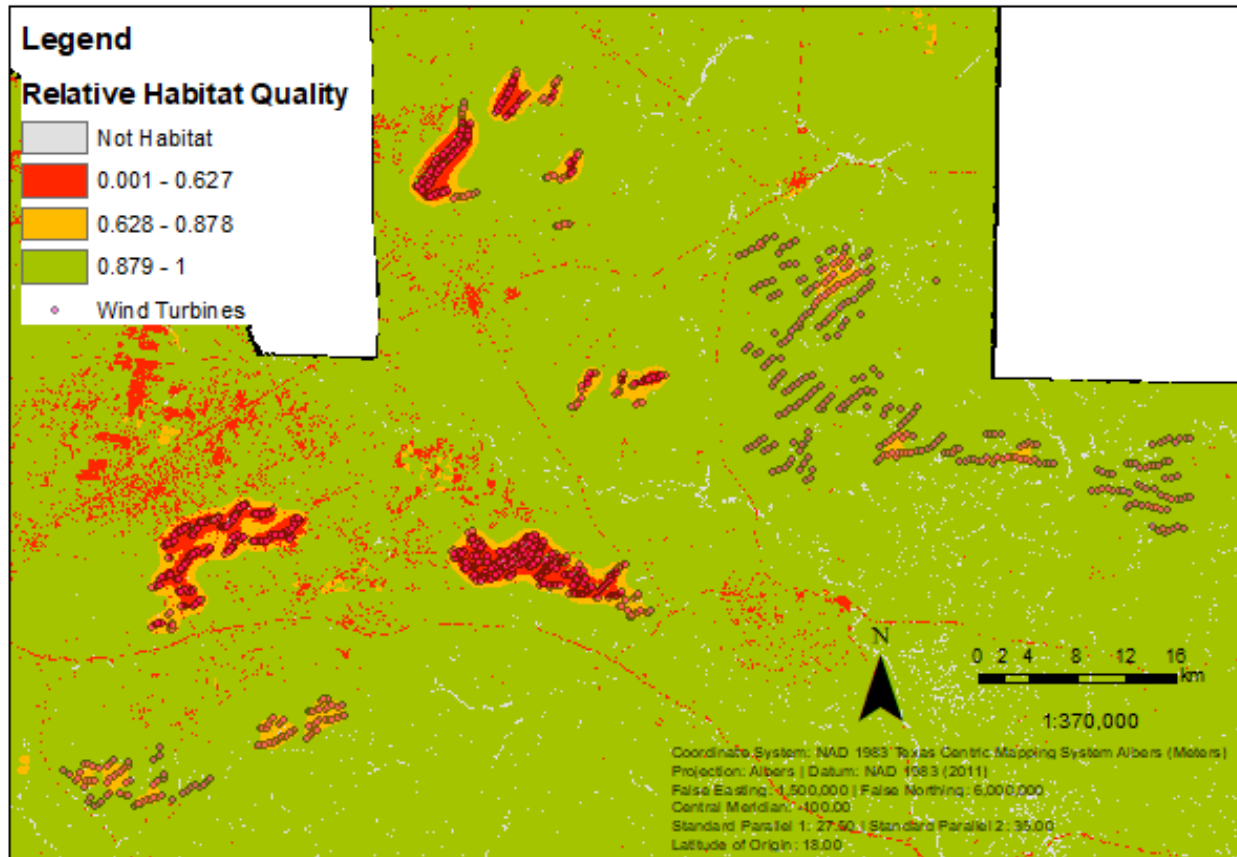
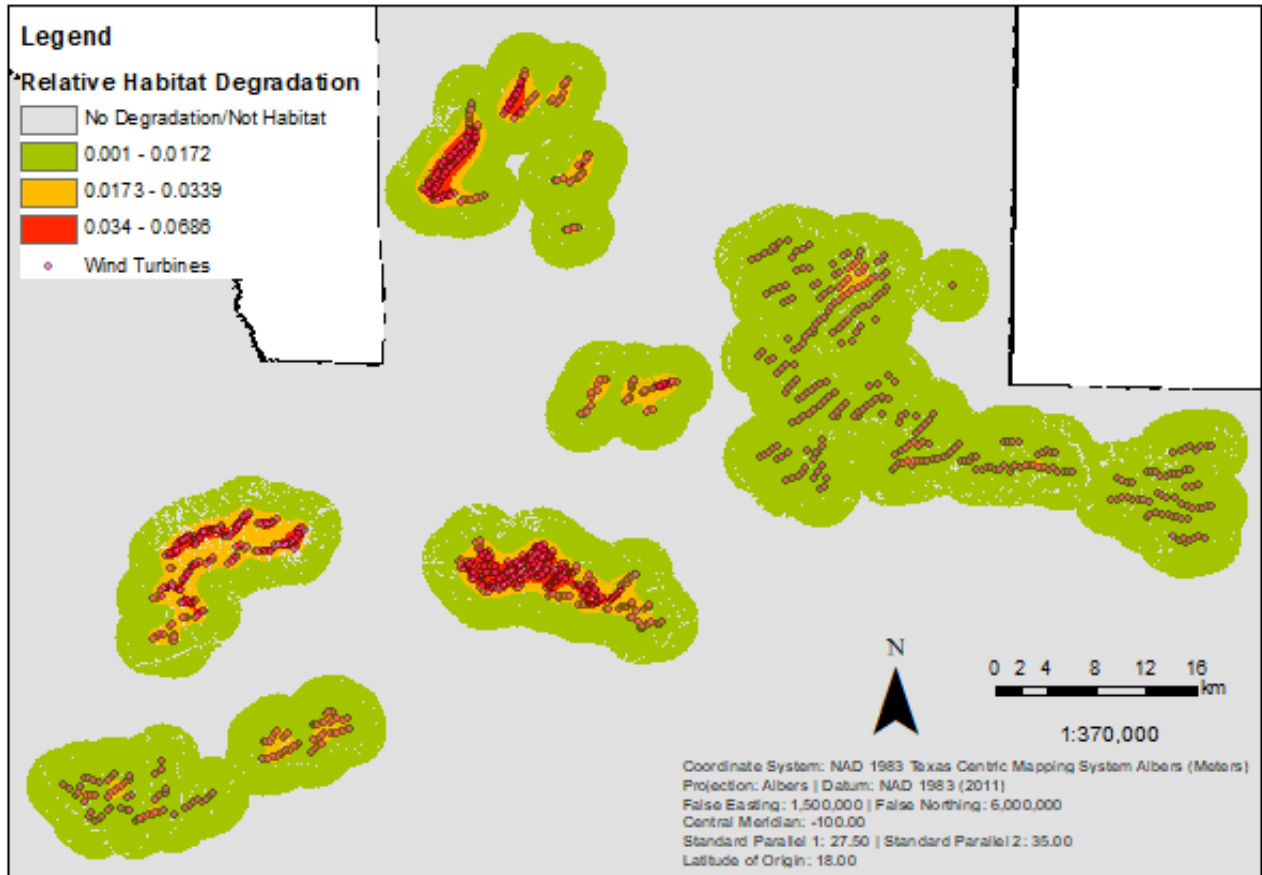


Figure 12. A magnified version of figure 10, showing relative habitat degradation results and wind turbine locations. Although all wind turbine strings are associated with some (>0) habitat degradation, many of the less-densely clustered turbines yield relatively low degradation values (<0.02), while densely clustered turbines have moderate-to-high degradation values.



Conclusions and Future Work

Relative habitat quality and habitat degradation raster generated by the InVEST Habitat Quality Model suggest that wind turbine installations may be associated with substantial habitat degradation/habitat quality reduction for the western Burrowing Owl. In particular, more densely clustered wind turbines correspond to higher, more spatially persistent degradation values.

One of the main strengths of the InVEST Habitat Quality model, as opposed to a fully GIS-based “map algebra”-style risk/hazard analysis, is the ability to easily incorporate multiple threats and decay models (e.g. exponential decay) that would pose challenges in GIS software. I plan to apply my approach from this project to other bird and bat species with varying habitat (land use) requirements in order to understand the differential impacts of wind turbines on unique species.

References

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