APPENDIX 1 – ENVIRONMENTAL PREDICTOR DATA

CONTENTS

Overview

We compiled a set of 60 potential predictor layers to use in distribution modeling for the target taxa. While some layers were available directly from data providers, most required at least basic processing to ensure that they matched the projection, extent, and cell size and alignment of “LULC_TX” land cover layer provided by TXNDD. All predictor data layers were originally created in ESRI GRID format and later converted to BIL and native Maxent-format rasters for use in modeling with Maxent software[1]. Predictor rasters used the “NAD 1983 Texas Centric Mapping System Albers (Meters)” projection (EPSG ID: 3083), and had a cell size of 30m.

Climate

Climate data comprised a set of 19 climatic layers representing monthly and quarterly temperature and precipitation means, ranges, and extremes[2], downloaded from the Worldlclim website (http://www.worldclim.org/) on June 24, 1013 (Table A1-1). These original data layers were in unprojected (i.e., geographic) coordinates, as ESRI-format rasters with a 30 arc-second cell size. Visual inspection of the predictor data layers revealed that two of the Bioclim layers, bio8 and bio9, exhibited artificially abrupt spatial shifts in their values due to the change in wettest/driest quarter from one quarter to the next. These two layers were therefore not included in the initial models that evaluated the relative performance and correlation between Bioclim predictors. Based on initial model runs for all taxa with only the Bioclim predictors and an assessment of variable collinearity, six variables -- shown in bold in Table A1-1 -- were included in the initial models for all taxa.

Table A1-1. Bioclim predictor variables. Predictors appearing in bold are those that were selected based on initial model runs using only Bioclim variables for all taxa.

Variable	Raster Name	Units	Number of Final Models Using Variable
Annual Mean Temperature	"bio1"	°C*10	-
Mean Diurnal Range (Mean of monthly (max temp - min temp))	**"bio2"**	°C*10	23
Isothermality (BIO2/BIO7) (* 100)	**"bio3"**	Dimensionless Index	24
Temperature Seasonality (standard deviation *100)	"bio4"	°C*100	-
Max Temperature of Warmest Month	"bio5"	°C*10	-
Min Temperature of Coldest Month	**"bio6"**	°C*10	27
Temperature Annual Range (BIO5-BIO6)	"bio7"	°C*10	-
Mean Temperature of Wettest Quarter	"bio8"	°C*10	-
Mean Temperature of Driest Quarter	"bio9"	°C*10	-
Mean Temperature of Warmest Quarter	**"bio10"**	°C*10	23
Mean Temperature of Coldest Quarter	"bio11"	°C*10	-
Annual Precipitation	"bio12"	Millimeters	-
Precipitation of Wettest Month	"bio13"	Millimeters	-

Variable	Raster Name	Units	Number of Final Models Using Variable
Precipitation of Driest Month	"bio14"	Millimeters	-
Precipitation Seasonality (Coefficient of Variation)	"**bio15**"	Dimensionless Index	27
Precipitation of Wettest Quarter	"bio16"	Millimeters	-
Precipitation of Driest Quarter	"bio17"	Millimeters	-
Precipitation of Warmest Quarter	"**bio18**"	Millimeters	25
Precipitation of Coldest Quarter	"bio19"	Millimeters	

HYDROLOGY

Hydrology variables represented two types of landscape-level measures of surface water availability: 1) distance to nearest water; and 2) prevalence of water within focal windows of 3 varying sizes (Table A1-2). These two types of metrics were chosen based on our previous modeling experience, in which different methods of representing surface water availability were more effective than others for particular taxa[3]. For example, we found that the locations for observations for waterbirds were often recorded at some distance away from water, where the observer stood when collecting a GPS point, leading to spurious relationships being identified by models when using the "distance to water" predictors.

Hydrology data layers were downloaded from the National GAP "Species Data" website (http://gapanalysis.usgs.gov/species/data/download/#hydrography) on July 11, 2013, and represented ordinal distance bands from surface water features[4,5]. We used a reclassification to convert this ordinal data to a binary, "water/not water" raster. We used the Euclidean Distance tool in ArcGIS with this binary water raster to generate the "Distance to All Water" layer. We then used the Focal Statistics tool with the same water layer, to find the proportion of cells within several specified neighborhood sizes that were mapped as surface water. The neighborhood sizes chosen -- 300m, 1600m, and 3200m – were those identified as being meaningful to a broad range of taxa in a previous modeling project[3].

Due to time constraints, we used a relatively straightforward and simplified approach for generating all hydrology layers, based on the readily available and precompiled data from GAP. More specific hydrology layers based on proximity to or prevalence of specific types of surface water (e.g., permanently flowing streams, intermittent pools, brackish water)[3] can be generated using data from the National Hydrology Dataset (NHD)[6], if knowledge of species biology suggests that this would be helpful.

Table A1-2. Hydrology predictor variables.

Variable	Raster Name	Units	Number of Final Models Using Variable
Distance to All Water	"allwatDist"	Meters	3
Prevalence of Water in a 1600m Neighborhood	"water1600"	Fractional value	1
Prevalence of Water in a 300m Neighborhood	"water300"	Fractional value	-
Prevalence of Water in a 3200m Neighborhood	"water3200"	Fractional value	3

LAND USE AND LAND COVER

Land use/land cover (LULC) predictor variables represented a variety of factors identified as potentially important for the modeling taxa (Table A1-3). Some of these variable layers were already available as raster data; others were created based one or more input data sources.

Table A1-3. Land use/land cover predictor variable

Variable	Raster Name	Units	Number of Final Models Using Variable
Agricultural Lands	"AgLand"	Binary	1
Human Impact Avoidance	"avoid"	Four ordinal categories; see Table A1-6, below	-
Average human impact in a 12800m window	"avoid12800"	Mean of "avoid" layer in 12800 m window	2
Average Human Impact in a 1600m Window	"avoid1600"	Mean of "avoid" layer in 1600 m window	1
Average Human Impact in a 3200m Window	"avoid3200"	Mean of "avoid" layer in 3200 m window	-
Average Human Impact in a 6400m Window	"avoid6400"	Mean of "avoid" layer in 6400 m window	1
Distance to Forest Edge	"d2foredge"	Meters	4
Distance to Forest/Woodland/ Shrubland Edge	"d2wlsl"	Meters	1
LANDFIRE Herbaceous Cover	"lfherbcc"	Percentage	7
LANDFIRE Shrub Canopy Cover	"lfshrubcc"	Percentage	12
LANDFIRE Forest Canopy Cover	"lfforstcc"	Percentage	3
LANDFIRE Existing Vegetation Height	"lf_evh"	Categorical	11
NLCD2001 Percent Tree Canopy	"nlcdcanopy"	Percentage	17

The LANDFIRE dataset[7] was the source for five of the LULC predictor variable layers. The Agricultural Lands layer was generated by reclassifying the LANDFIRE Existing Vegetation Cover (EVC) layer[8], downloaded on July 9, 2013 from http://www.landfire.gov/vegetation.php , into a binary raster (1=agricultural land cover types – see Table A1-4; 0=all other types). This raster was used as a categorical predictor variable for species that might avoid agricultural lands in otherwise suitable environmental settings.

Table A1-4. LANDFIRE land cover/land use types included in the Agricultural Lands layer reclassification.

Value	LANDFIRE Existing Vegetation Cover Type
60	NASS-Orchard
61	NASS-Vineyard
62	NASS-Bush fruit and berries
63	NASS-Row Crop-Close Grown Crop
64	NASS-Row Crop
65	NASS-Close Grown Crop
66	NASS-Fallow/Idle Cropland
67	NASS-Pasture and Hayland
80	Agriculture - General
81	Pasture/Hay
82	Cultivated Crops
83	Small Grains
84	Fallow

The same LANDFIRE EVC[8] dataset also provided useful measures of herbaceous cover, shrub canopy cover, and forest canopy cover. To generate raster layers representing each of these attributes, we performed three reclassifications on the EVC layer using the midpoints of the percent cover estimates for each vegetation level (i.e., herbaceous, shrub, and forest) represented by the EVC categories (Table A1-5). Lastly, we also used the Existing Vegetation Height (EVH) layer[9] from LANDFIRE as a potential predictor for taxa thought to respond to vegetation structure.

Table A1-5. Reclassification table for the herbaceous ("lfherbcc"), shrub ("lfshrubcc"), and forest ("lfforstcc") cover estimate layers derived from the LANDFIRE EVC layer.

Value	LANDFIRE Existing Vegetation Cover Type	"lfherbcc" Output Value	"lfshrubcc" Output Value	"lfforstcc" Output Value
121	Herb Cover >= 10 and < 20%	15	0	0
122	Herb Cover >= 20 and < 30%	25	0	0
123	Herb Cover >= 30 and < 40%	35	0	0
124	Herb Cover >= 40 and < 50%	45	0	0
125	Herb Cover >= 50 and < 60%	55	0	0
126	Herb Cover >= 60 and < 70%	65	0	0
127	Herb Cover >= 70 and < 80%	75	0	0
128	Herb Cover >= 80 and < 90%	85	0	0
129	Herb Cover >= 90 and <= 100%	95	0	0
111	Shrub Cover >= 10 and < 20%	0	15	0
112	Shrub Cover >= 20 and < 30%	0	25	0
113	Shrub Cover >= 30 and < 40%	0	35	0
114	Shrub Cover >= 40 and < 50%	0	45	0
115	Shrub Cover >= 50 and < 60%	0	55	0
116	Shrub Cover >= 60 and < 70%	0	65	0
117	Shrub Cover >= 70 and < 80%	0	75	0
118	Shrub Cover >= 80 and < 90%	0	85	0
119	Shrub Cover >= 90 and <= 100%	0	95	0
101	Tree Cover >= 10 and < 20%	0	0	15
102	Tree Cover >= 20 and < 30%	0	0	25
103	Tree Cover >= 30 and < 40%	0	0	35
104	Tree Cover >= 40 and < 50%	0	0	45
105	Tree Cover >= 50 and < 60%	0	0	55
106	Tree Cover >= 60 and < 70%	0	0	65
107	Tree Cover >= 70 and < 80%	0	0	75
108	Tree Cover >= 80 and < 90%	0	0	85
109	Tree Cover >= 90 and <= 100%	0	0	95
-	All other types	0	0	0

Each potential predictor layer may be of varying accuracy in different areas or types of settings, or may represent a particular attribute in a somewhat different manner. It is therefore beneficial in some cases to incorporate multiple sources of data for important predictor layers. Forest canopy cover is an important attribute for many plant and animal species, we used a second estimate of forest canopy cover from the National Land Cover Dataset (NLCD)[10], in addition to the LANDFIRE layer described above. This layer was provided by TXNDD, and was resampled to match the other predictor data layers. The LANDFIRE forest canopy cover appears to provide more detailed mapping of canopy cover in the eastern portion of the state, but does not map any forest canopy cover in some portions of central and western Texas where the NCLD forest canopy cover layer does. Thus, both layers were included as potential predictor layers for taxa that might either occur preferentially within or avoid forested areas. Because the two forest canopy cover estimate layers were highly correlated with one another, we chose to include only the layer with the highest percent contribution value.

We incorporated five layers representing human impact on the landscape, for taxa that might be sensitive to human presence or development. The original source dataset was the "Human Impact Avoidance" layer prepared and distributed by the National GAP office[11]. This layer was incorporated directly, as a categorical variable, in models for taxa that our research indicated are most averse to human presence or development. However, since categorical data are often problematic in modeling, we also generated indices representing the relative human impact level on the landscape at four nested neighborhood sizes: 1600m, 3200m, 6400m, and 12800m. These landscape-level layers were generated by finding the mean value of the "avoid" layer within circles with radii corresponding to the chosen window sizes, using the Focal Statistics tool in ArcGIS. Values in these layers ranged from 0 to 3, with the highest values occurring in the center of large, developed areas, and the lowest values occurring in areas with little human development nearby.

Table A1-6. Impact ratings from the GAP "Human Impact Avoidance" layer.

"Avoid" Layer Value	Human Impact Level
0	None
1	Low
2	Moderate
3	High

We generated two additional, landscape-scale predictor variables related to LULC, also based on datasets from the National GAP office[12]. As with the hydrography dataset, the original GAP datasets – "Forest Edge" and "Forest/Open Ecotone + Woodlands/Shrublands" – are ordinal datasets describing distance bands within or away from these two types of ecotones. Since most modeling software will interpret ordinal categories as unordered categories, thereby discarding useful information, we generated a continuous representation of "distance to ecotone" based on each of these source datasets. To do this, we first reclassified each of the datasets so that the ecotone boundaries received a value of 1, and all other cells in the original rasters received NoData values. We then used the Euclidean Distance tool in ArcGIS to calculate the distances within and away from these ecotone boundaries, in meters. Negative values in the output layers represent distances measured from the edge of the ecotone boundary *inward* for forest and forest/woodland/shrubland patches, for the "d2foredge" and "d2wlsl" layers, respectively, while positive values represent distances measured *away* from the edges of these patches.

SOILS AND SUBSTRATE

Soil characteristics are extremely important in shaping distributions for many plant and animal species, but can be difficult to represent with data of sufficient spatial resolution to be useful[13]. The Soil Survey Geographic (SSURGO) database[14] is a digital representation of county level soil data prepared and distributed by the Natural Resources Conservation Service (NRCS). This dataset contains a geographic representation of soil map units (SMU) and relational tables describing various components of each SMU, and can be used to generate a large number of potentially useful GIS layers via the Soil Data Viewer (SDV) tool[15]. Unfortunately, SSURGO databases are distributed on a county-by-county basis. As there are 254 counties in Texas, downloading, compiling, and processing SSURGO data for all counties was not practical within the scope of this project.

Instead, we were able to use Gridded SSURGO (gSSURGO) dataset[16], in conjunction with custom Python scripts provided by NRCS staff (Steve Peaslee, pers. comm.), to generate many of the potential predictors we identified during our initial species review work (Table A1-7). These scripts summarize pertinent attribute information from the component or horizon-level tables in the SSURGO database, providing output comparable to what the SDV tool produces using SSURGO data. Continuous soil predictors were generated the "weighted average" approach, which summarizes measurements of the attribute in question at the SMU level, based on the prevalence of each of the components that comprise each SMU. Ordinal soil predictors were summarized using the "dominant condition" approach, which assigns the category that appears most commonly across all components in the SMU.

Table A1-7. Soil predictor variables.

Variable	Raster Name	Units	Number of Final Models Using Variable
Hydrologic Soil Group	"hydgroup"	Ordinal rating of runoff potential from low (A;0) to High (D;3)	1
Saturated Hydraulic Conductivity	"ksat"	Micrometers per second	2
Soil Drainage Class	"drainClass"	Ordinal rating of drainage, from excessively drained (0) to very poorly drained (6)	7
Soil Electrical Conductivity	"soilEC"	Millimhos per centimeter at 25° C	2
Soil pH	"soilph"	pH rating	4
Total Percent Clay	"percClay"	Percentage	8
Total Percent Sand	"persSand"	Percentage	13
Total Percent Silt	"percSilt"	Percentage	2

Hydrologic Soil Group and Soil Drainage Class are both ordinal ratings of soil moisture. Hydrologic Soil Group measures runoff potential, whereas Soil Drainage Class indicates how well soils are drained. Saturated Hydraulic Conductivity is a continuous measure of the ability for moisture to move through saturated soils. These three metrics all describe related soil moisture attributes and correlate highly across most SMUs. However, as with the forest canopy cover datasets, for specific taxa each of these predictors appeared to be more useful than the others. We included only the predictor from this set of three that had the highest percent contribution for a taxon's model.

Soil chemistry is particularly important for many plant taxa. Soil Electrical Conductivity, a measure of soil salinity, and soil pH are particularly important attribute for plants in many basin and grassland ecosystems. Total percent clay, sand, and silt predictors provide a complete picture of soil textures at the SMU level, and were identified as useful predictors for many of the modeling taxa.

In addition to the soil predictors described above, there were five soil predictors identified by our initial species review that we were not able to generate. Calcium carbonate content, effective cation-exchange capacity, gypsum content, and depth to shallowest restrictive layer (i.e., soil depth) all capture information on potentially important soil attributes for our modeling taxa. We were not able to generate these layers due to errors encountered with the Python scripts provided by NRCS staff. In some cases these errors were due to the fact that some attributes are not summarized in the "Value Added" tables that accompany the gSSURGO data, and in other cases appear to have occurred because attribute data may be stored at the horizon level, rather than at the component or SMU level.

TERRAIN

Terrain generally influences distribution in an indirect manner. For example, slope, aspect, curvature, and dissection all measure various facets of topography that can influence available site moisture at a fine scale. While there are a large number of potential predictor data layers that can be generated from a single, raster elevation dataset[17-20], we chose a set that we felt covered the most important characteristics of terrain and that have proven useful in previous modeling efforts (Table A1-8)[3,21].

Table A1-8. Terrain predictor layers.

Variable	Raster Name	Units	Number of Final Models Using Variable
A-prime, Measured Along Northwest to Southeast Axis	"aprime135"	Index ranging from 0 (Northwest) to 2 (Southeast)	0
A-prime, Measured Along North to South Axis	"aprime180"	Index ranging from 0 (North) to 2 (South)	0
A-prime, Measured Along Northeast to Southwest Axis	"aprime45"	Index ranging from 0 (Northeast) to 2 (Southwest)	2
A-prime, Measured Along West to East Axis	"aprime90"	Index ranging from 0 (West) to 2 (East)	1
Compound Topographic Index	"CTI"	Dimensionless index	0
Curvature Within a 10-cell Window	"curve10"	Dimensionless index	0
Curvature Within a 5-cell Window	"curve5"	Dimensionless index	1
Dissection Within a 10-cell Window	"dissect10"	Dimensionless index	7
Dissection Within a 5-cell Window	"dissect5"	Dimensionless index	9
National Elevation Dataset (30 m)	"ned"	Meters	7
Radiation loading	"radld"	Dimensionless index	1
Slope	"slope"	Degree	3
Vector Ruggedness Measure (VRM) with 10-cell window	"vrm10"	Dimensionless Index	4
Vector Ruggedness Measure (VRM) with 5-cell window	"vrm5"	Dimensionless Index	2

We downloaded 1 arc-second (approximately 30 m) National Elevation Dataset[22] tiles for Texas, and mosaicked them to generate a single elevation dataset ("ned") for the state with a cell size and extent matching that of the other predictor data layers. Elevation generally only influences distribution in indirect ways, typically by influencing climatic gradients to which taxa respond[13], and was therefore only directly included in the initial models for taxa we felt might be well represented by this predictor.

Slope (i.e., steepness) can directly influence the distribution of species like Bighorn Sheep (*Ovis canadensis*) that prefer steep topography, or species like Mountain Plover (*Charadrius montanus*) that *avoid* steep topography. It can also indirectly influence distribution by influencing site moisture, solar radiation, and other important environmental factors. We generated a degree slope layer from the "ned" layer using the Slope tool in ArcGIS.

Slope aspect can be an important terrain characteristic, as it influences a number of potentially limiting or controlling factors in a variety of ways. First, aspect can strongly influence radiation loading, temperature, and moisture along a southwest (dry, hot) to northeast (cool, moist) gradient[23]. Second, aspects representing predominantly windward or leeward sides of even relatively small hills or other topographic features provide different environmental conditions due to soil and snow deposition and deflation. Aspect is of relatively limited direct usage in modeling, since, as a cyclical variable, two very different values (e.g., 359 and 1) represent very similar aspects. Thus, we used a standard technique for transforming raw aspect values into continuous gradients, referred to as *A-prime*[23], along four major axes (see Table A1-8). "Aprime45" is the most commonly used transformation based on this method, and represents a moisture and temperature gradient.

Since the effect of aspect on solar radiation, and the associated moisture and temperature gradients, varies depending upon the slope (i.e., steep southwest slopes are warmer and drier than areas of similar aspect with lower slopes), we multiplied the "Aprime45" layer by the slope layer, to create a layer, "radld," that represents this interaction between aspect and slope in modifying radiation and site moisture. Site measure can also be measured as a function of the ratio of upstream contributing area to slope, known as the Compound Topographic Index (CTI)[17,18]. We generated a CTI layer based on the "ned" dataset, using the Geomorphometry & Gradient Metrics (version a1.01) toolbox provided by staff at The Nature Conservancy (TNC; Jeffrey Evans, pers. comm.).

As with slope, various taxa prefer different levels of terrain ruggedness. While a number of measures exist to quantify ruggedness[24-28], we selected the Vector Ruggedness Measure[29], as it has proven useful for us in past modeling efforts[3]. This measure quantifies ruggedness by measuring variance three-dimensional distances within a user-specified neighborhood, and is less correlated with slope than other ruggedness measures[29]. We selected window sizes of 5 and 10 raster cells to quantify ruggedness within 150 and 300m windows, respectively.

Slope curvature measures describes the concavity or convexity of terrain, and provides an indication of landform shape that has been shown to correlate with vegetation height[30,31]. Dissection measures the relative position of cells on landforms, with the lowest values in deep depressions or valleys and the highest values on top of high ridges or hills[19]. We generated both curvature and dissection layers using window sizes of 5 and 10 raster cells using TNC's Geomorphometry & Gradient Metrics (version a1.01) toolbox and the "ned" dataset.

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