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A GIS Model to Predict Feral Pig (Sus scrofa) Habitat on Vandenberg Air Force Base, California

Brian Schnick

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Brian Schnick
Capstone Project
University of Denver

Disclaimer

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Natural Resource Area

The applicable Natural Resource area of this project is animal control and wildlife management, as wild pigs can be quite destructive to landscapes (Campbell, et al., 2010) (McCann, et al., 2008). Geographic Information System (GIS) predictive models have proven to be useful in regards to other mammals (Travaini, et al., 2007), raptors (Bustamante, et al., 2004), and pest species such as locusts (van der Werf, et al., 2005). Pigs are often nocturnal and bed down in heavy cover, hindering direct observation. Additionally, Vandenberg Air Force Base (VAFB) encompasses over 400 square kilometers. Therefore, predictive modeling is an appropriate method for identifying areas likely to be inhabited by pigs, and when combined with a ranked collection of valued property, the model should prove to be a valuable resource for planning and allocating animal control measures.

Proposed Audience

The 30th Civil Engineering Squadron (CES) is charged both with the management of the installation's real property and wildlife population. Archeologists employed by the base have identified approximately 1,600 cultural resource sites on Vandenberg AFB property. Some of these sites contain artifacts that are carbon dated as being up to 10,000 years old. Most facilities on the installation are surrounded by some form of landscaping, and the golf course in particular is a business that depends on maintaining healthy grasses and a smooth ground surface. This model may provide valuable information to biologists, archeologists, and wildlife conservation officers as they seek to manage their various assigned resources in a comprehensive, sustainable manner.

Needs Assessment

Pigs were first introduced to California by Spanish missionaries in the 18th century and later by ranchers in the 1920s (Pine and Gerdes 1973, Mayer and Brisbin 1991). They currently inhabit 56 of California's 58 counties (Waithman 2001).

Feral pigs are known to cause damage, both to ecology and economy (McCann, et al., 2008), primarily through the activity of rooting. VAFB has experienced damage to both landscaped areas including lawns and the golf course, as well as to archeological sites caused by rooting feral pigs. Rooting is a method of obtaining grubs and roots of vegetation for food, where pigs use their snouts to dig 6 to 18 inches into the ground. This rooting activity destroys landscaping and archeological sites, kills turf, and leaves furrows that are expensive to repair. Pig activity threatens the unarmored three spine stickleback fish, an endangered species, in San Antonio creek due to both the disruption of water flow caused by wallowing in the creek bed, as well as from increased soil runoff from disturbed land draining into the creek.

Currently, no meaningful systematic collection of data on feral pig distribution is in place. Pig hunters who take animals from base property are required to report the location of their kill to the conservation officers, however these reports are highly generalized and include entries such as 'in area 4', which describes approximately 64 square kilometers. A substantial amount of information resides in the personal memory of subject matter experts, such as some conservation officers who have worked in this area for approximately six years. The range manager, archeologists, and game conservation officers desire a means to better understand the behavior of feral pigs and a method to predict where the pigs are likely to cause damage.

Goal of Application

The goal of this application is to create a predictive model of feral pig habitat on Vandenberg AFB. The model will be based on the preferred habitat of feral pigs as well as data collected from a sample area on base property (Waithman, 2001). The model will provide predictions on likely areas of pig habitat and therefore provide a means to predict areas most likely to sustain damage. This information could then be compared to a listing of archeological sites, ranked in order of perceived value of site artifacts, so as to prioritize either the sequence of study of the sites or to select sites for animal control measures. The predictions could possibly be used by conservation officers, landscapers, and the golf course superintendent to plan preventative measures. Passive animal control measures include erecting barriers or modifying habitat to discourage intrusion to valuable property. Possible active measures include trapping, relocating, euthanizing, and adjusting hunting limits in targeted areas or considering incentives to use hunting as a means of animal control.

Figure 1: Animal Trap (USAF, 2010)

Software Requirements

The 30th CES GIS workstations are standardized with ArcMap 9.3 software from Environmental Systems Research Institute (ESRI), with a collection of ArcView and ArcInfo licenses. Included in ESRI's software suite is a server product called ArcSDE, or Spatial Database Engine, which manages spatial data in a relational database management system. The Information Technology Department set Windows Vista and Microsoft Office 2007 as the respective standard for desktop operating system and productivity suite.

Within ArcMap, the Spatial Analyst extension is used to access the Raster Calculator functions, which are used to create a Map Algebra statement to combine selected raster files to create an animal distribution prediction. Other Spatial Analyst tools used are Extract Values to Points, which is used to identify environmental values from various raster layers on the basis of the GPS point data; and Distance Straight Line, which is used to create rasters measuring the distance to both roads and water features. Finally, the command ReclassByASCIIFile_sa was used from the ArcMap command line to reclassify nominal land cover values into ordinal raster data.

Hardware Requirements

The Civil Engineering Squadron possesses a Windows 2008 server with ArcSDE on a Oracle 11g platform, and numerous Dell desktop workstations. These workstations are used by the Geobase manager, GIS/Global Positioning System (GPS) shop, and the natural/cultural resources division (range manager, archeologists, and biologists) to operate ArcMap. Additionally, there is an ArcIMS application with selective layers available to all users of the base WAN.

A variety of government owned sensing methods were available. A Trimble GeoXH handheld GPS unit (Figure 2) was used to mark presence and absence points along walked transects. Infrared thermography is useful for detecting state of health (Dunbar and MacCarthy, 2006) and estimating populations of animals (Blackwell, et al., 2006). A Raven unmanned aerial vehicle (Figure 3, 4) with an infrared sensor was flown to determine if wild pigs may be detected and counted using this system. During a 1-hour demonstration flight, it was determined that the UAV can scan sample areas much quicker that by foot, and is especially useful for covering terrain that is either impassible due to slope or vegetation density, or is off-limits due to potential unexploded ordinance. Motion-triggered still cameras were employed for two weeks. Spotlights and night vision goggles were available to detect nocturnal animal activity, but neither was used due to time constraints.

Figure 2: Trimble GeoXH Handheld GPS (Trimble, 2010)

Figure 3: Raven UAV (wpclipart.com, 2010)

Figure 4: UAV Visible light image (USAF, 2010)

Datasets and Sources

The source of secondary environmental data for this project is the National Map Seamless Server, and all such data is available from U.S. Geological Survey, EROS Data Center, Sioux Falls, SD, or at http://seamless.usgs.gov/website/seamless/viewer.htm. This server allows the simultaneous selection of multiple data layers in the same projection/coordinate system, which ensures proper alignment with minimal data conversion. The specific layers used in this project are:

BTS Roads	NED 1/9 arc sec	NAIP (3 band) UTM Zone 10
NLCD 2001 Land Cover (30m)	National Atlas Vegetation Growth – Peak:2005	National Atlas Vegetation Growth – Average:2005
National Atlas Roads	National Atlas Streams	National Atlas Land Cover Characteristics (AVHRR 1km)

Table 1: GIS Layers Used (USGS, 2010)

Primary feral pig location data was collected from May 1st to 3rd , 10th to 12th, and 18th to 20th, 2010, using a Trimble GeoXH handheld GPS device to mark the locations of pig scat, tracks, wallows, rooting, and beds in seven 1km^2 sample areas. The base property includes just over 400 square kilometers. A sample frame of 36 square kilometers (6km x 6km) was selected based on the rich variety of environmental features contained within it, which represents all micro-climates on base except beaches. From this sample frame, nine 1km^2 sample areas were selected using multi-stage area sampling: three 3x3 blocks of 1km^2 cells each had 3 cells randomly selected from within (Figure 5). Three transects were assigned for each sample area, with the proportion of North-South vs. East-West transects selected randomly. The 1km^2 area was numbered in 100 meter increments both horizontally and vertically starting at the southwest corner of each cell. Finally, the position of the transect within the sample area was randomly selected from these possible locations. The website www.random.org was used to generate all random numbers required for sample selection. This method is superior to pseudo-random generators, as it uses atmospheric noise to produce truly random results.

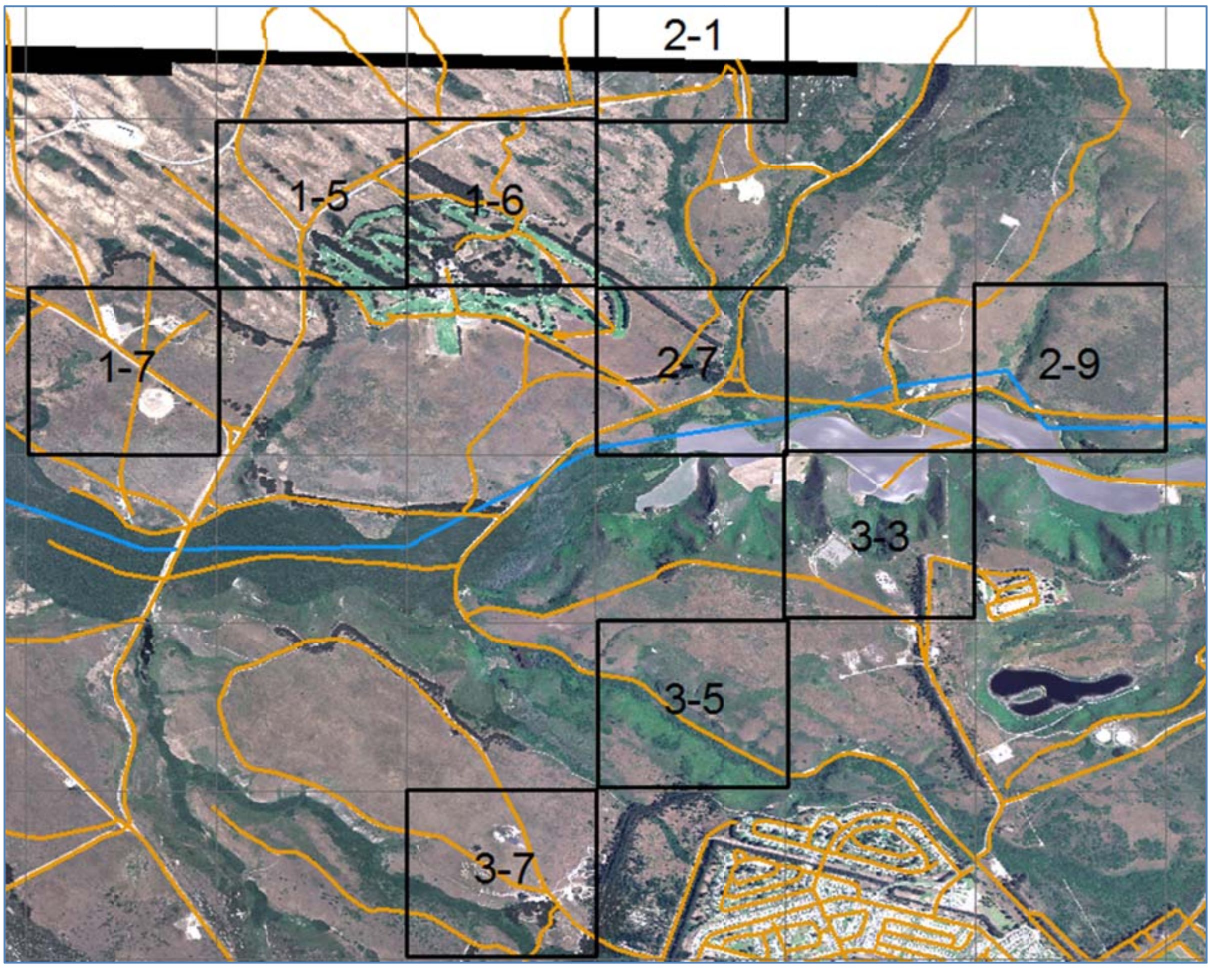

Figure 5: Sample Areas

Upon visiting the sample areas, it was found that the entirety of two areas (1-7 and 2-9) were closed to access due to Explosive Ordinance Disposal operations, and that three additional areas (2-7, 3-3, and 3-7) contained significant inaccessible portions due to prohibited areas, impassible brush, and steep slopes. Due to time constraints, these areas and portions of areas were rejected without replacement. While walking the transects, ground up to 1m on each side of the path was considered, to the extent visibility allowed. GPS points were collected approximately every 100 meters if no sign was noted, or at the location of each scat, track, wallow, root, or bed. The CES standard for GPS field data collection is to collect and average a minimum of 45 fixes per point collected. This yielded a post-processed average accuracy of 30cm per the unit's display, or approximately 90cm real-world accuracy, as verified by geodetic monuments. Fifty-four points indicating pig presence were recorded, and forty-seven points were recorded that lacked indicators of presence.

A Leaf River DC-6SS digital game camera (Figure 6) was placed beside game trails in area 2-7 from June 21st to 26th and in area 2-1 from June 29th to July 5th. The camera's controls include settings for light condition (day, night, both), length of pause between pictures, number of pictures per trigger event, and trigger sensitivity. With multi-day employments, it can therefore take considerable time to discover a productive methodology using this sensor. The results realized were 120 photos of brush moving in the wind, and one night photo of a deer.

Figure 6: Leaf River Digital Game Camera (Leaf River Outdoor Products, 2010)

The Raven UAV was flown on July 29th for two hours immediately after sunset using an infra-red sensor to scan areas 1-5, 1-6, 2-4, 1-8, 1-9, 2-7, 3-1, 3-2, and 3-3. Six moving targets were noted in area 3-2, but the sensor did not have enough resolution to determine what the objects were. An inspection of the target area the following day revealed numerous game trails, beds, and fresh pig and deer tracks (Figure 7). The objects viewed by the UAV were assumed to be pigs and their locations included as presence points, although definitive confirmation of their identity was not possible.

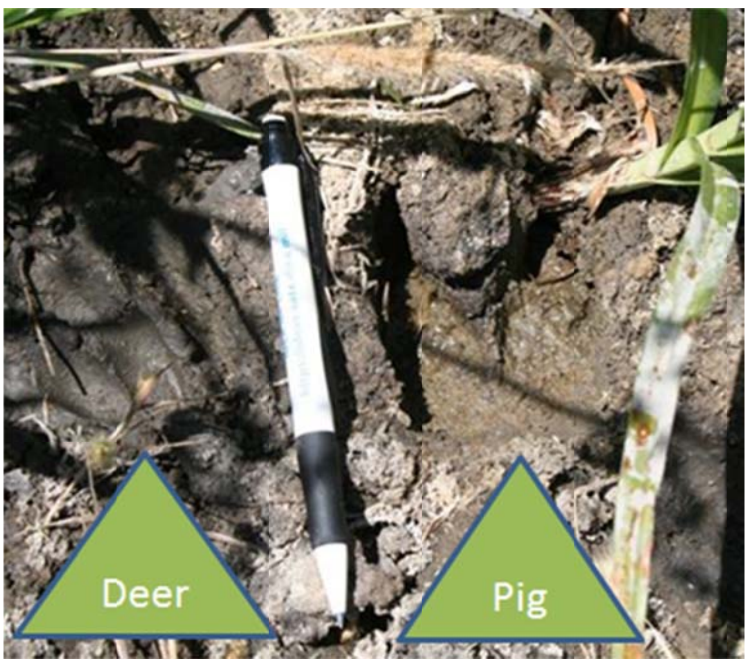

Figure 7: Tracks in area 3-2

Application Development

It is hypothesized that feral pig distribution will be positively affected by proximity to water and certain vegetation , and negatively by proximity to roads, commercial and industrial areas (Zarri, et al., 2008)(Waithman, 2001). The specific attractiveness values used for National Land Cover Data (NLCD) categories follows:

NLCD	Name	Weight
11	Open water	1
21	Urban, recreational grasses	2
22	Low intensity residential	2
23	High intensity residential	1
24	Commercial, industrial, roads	1
31	Transitional barren	1
42	Evergreen forest land	2
43	Mixed forest land	2
52	Shrub land	3
71	Grasslands, herbaceous	3
90	Woody wetlands	3
95	Emergent, herbaceous wetland	3

Table 2: NLCD Weights

The original NLCD raster was reclassified in ArcMap at the command prompt using the statement “ReclassByASCIIFile_sa NLCD_2001_30m c:/Reclass2/reclass2.txt c:/Reclass2/NLCD_reclass2 DATA”, with the reclass2.txt file containing the NLCD Code and Weight values from the above table. The following expression was used in Raster Calculator to combine the three input rasters (Distance to water, Reclassified NLCD data, Distance to roads) into a prediction raster (Figure 8):

```
((([Dist2SmWaRas2] * -0.000114) + 1) * 6) + (([Dist2RoadRas] * 33.33) * 4)+ ([nlcd_reclass] * 0.33)
```

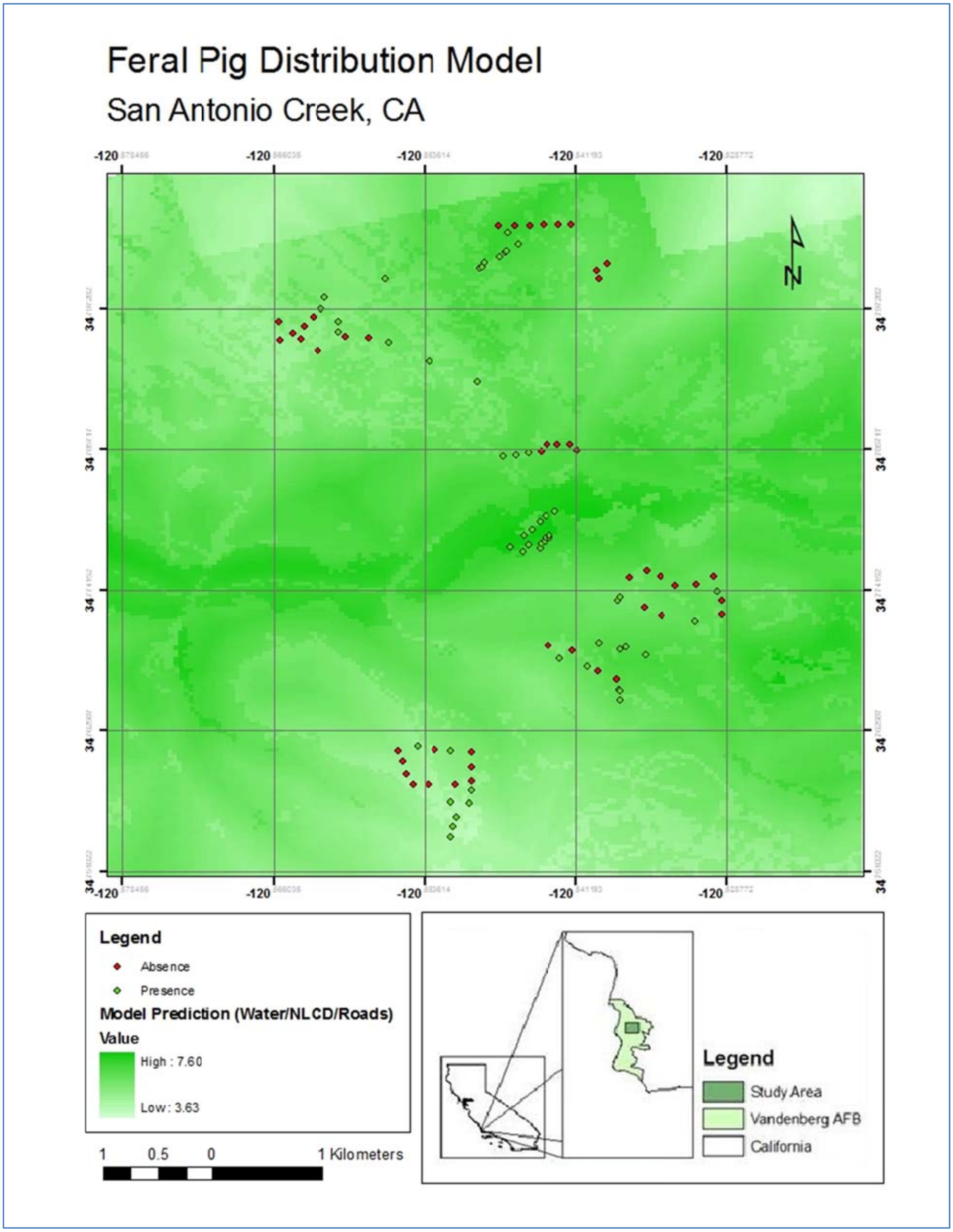

Figure 8: Feral Pig Distribution Model

The GPS points and the associated environmental information were collected into a table (Table 3), and summarized in graphs (Figure 9). The graphs show that the Presence points tended to be farther from roads, closer to water, and favoring herbaceous grasses when compared to the Absence points. The table was analyzed by JMP 8 statistical software using logistic regression (Travaini, et al., 2007)(Zarri, et al., 2008). The logistic regression yielded a fit with an R-squared value of 0.04, indicating no meaningful correlation between the environmental data and the presence of pig indicators.

A second set of presence/absence data was fabricated to validate the statistics analysis process (Figure 10). This fictional data included 108 points spread approximately evenly throughout the entire sample area, with points marked as presence or absence based subjectively on the trends that emerged during the course of the study: feral pigs show an affinity to wetland vegetation and the associated water features, and are only slightly averse to roadways. The same JMP 8 regression steps yielded an R-squared value of 0.31, showing that the selected indicators (water, vegetation, and roads) are valid for predicting feral pig presence.

Finally, a correlation analysis was done in Excel between each data point's Presence/Absence value (1 or 0, respectively), and the prediction value assigned to the point by the model. The formula showed a correlation of 0.22, indicating a weak positive agreement between the model and ground truth data. Interestingly, the simulated data's correlation to the model's prediction was only 0.11.

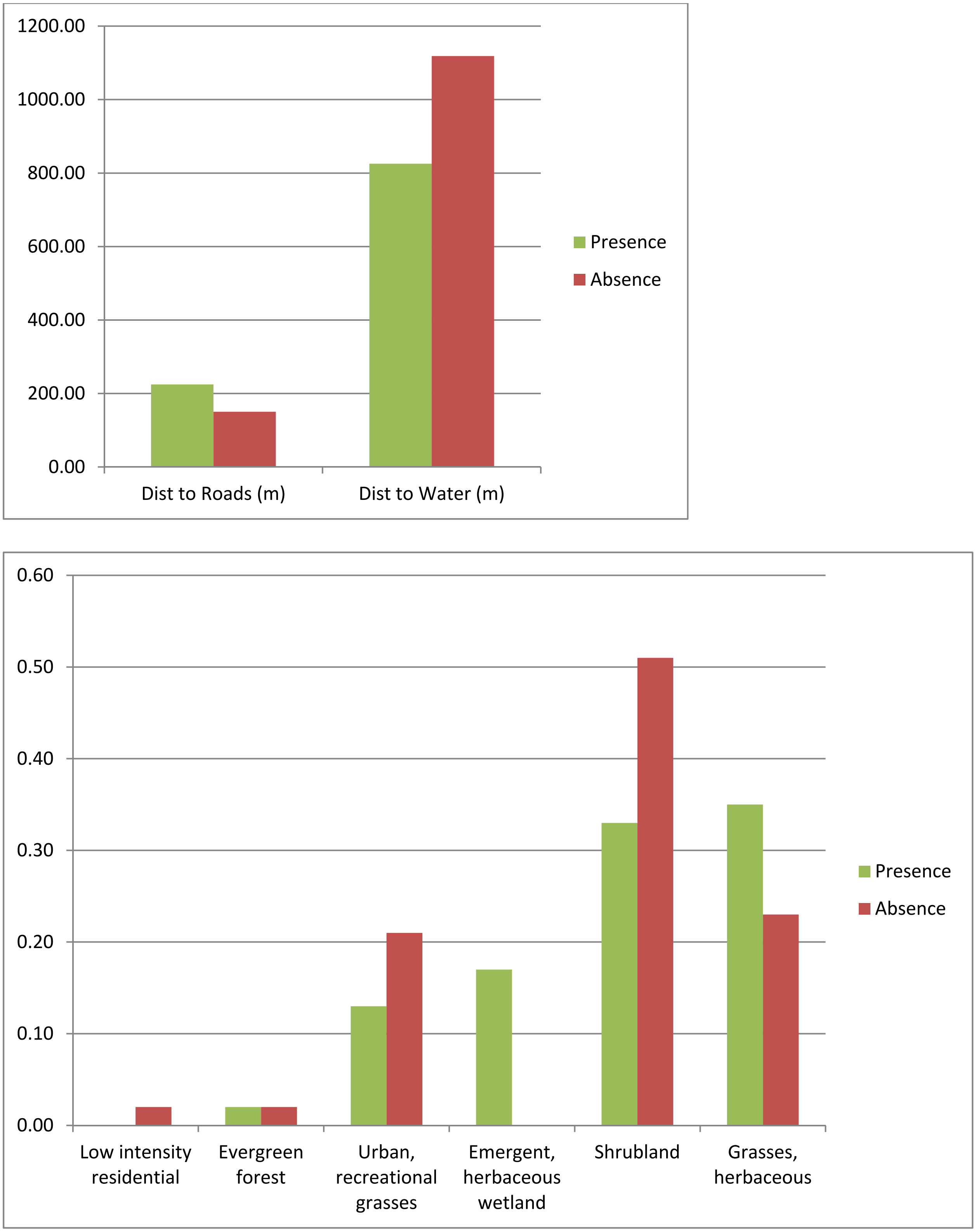

Figure 9: Summary of Environmental Data

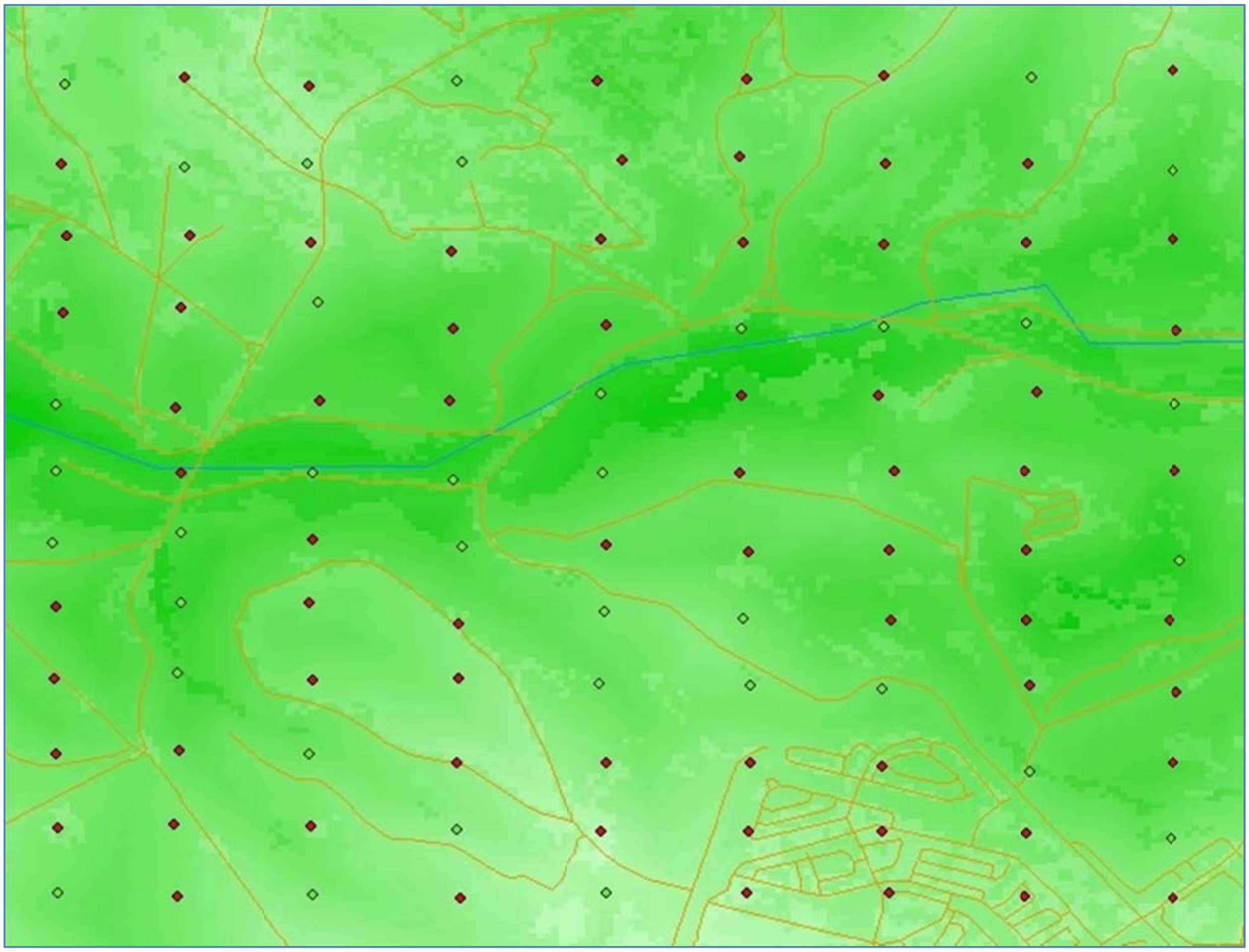

Figure 10: Simulated Data

Discussion

A model for predicting feral pig distribution was created based on the environmental factors of distance to water, the location of various vegetation types in the study area, and distance to roads. The three factors were weighted (60% water, 30% vegetation, and 10% roads) according to their perceived influence on pig habitat selection. To test the validity of the model, data was collected through field observation on the presence or absence of feral pigs, and the environmental characteristics of each point was determined.

The data collected failed to prove or disprove the validity of the selected environmental indicators (Distance to water, vegetation, and Distance to roads) due to the presence data and absence data being statistically indistinguishable, although the statistics analysis process was validated using simulated data. Ultimately, the model was moderately successful in predicting feral pig presence. Previous research noted numerous obstacles to creating GIS models for predicting animal distributions, including design, data collection, imperfect species detectability, and the expensive in both time and money of field data collection (Travaini, et al., 2007). The primary limiting factor in this project was difficulty in gathering sufficient observational data in the time allotted.

Future research should expand the data collection effort, and this effort should be dispersed versus concentrated (Carlson, et al. 2002). All available means, including still cameras and night vision devices, but most especially the infrared UAV sensor, should be employed to increase 'ground truth' data. It cannot detect presence indicators such as tracks, scat, and beds, and the low resolution infra-red images must be verified by alternate means.

This sensor does however, have the ability to overcome the vegetation, slope, and administrative barriers posed to walking ground transects.

Ultimately, radio collars could be employed to provide irrefutable presence data. Once the model is further refined and verified with observational data, the wildlife distribution prediction will be compared to the location of archeological sites and high-valued landscaping in order to prioritize wildlife-induced damage control efforts. Additionally, the effects of seasonal changes in vegetation on pig distribution could be explored.

Table 3: Attributes of GPS point data

Presence	Dist to Roads (m)	Dist to Water (m)	Urban, recreational grasses	Low intensity residential	Evergreen forest	Shrubland	Grasses, herbaceous	Emergent, herbaceous wetland
1	0	590	1	0	0	0	0	0
1	0	2497	1	0	0	0	0	0
1	0	2409	1	0	0	0	0	0
1	0	2197	1	0	0	0	0	0
1	0	1210	1	0	0	0	0	0
1	0	1032	1	0	0	0	0	0
1	0	1005	1	0	0	0	0	0
1	0	2337	0	0	1	0	0	0
1	281	1028	0	0	0	1	0	0
1	373	1442	0	0	0	1	0	0
1	460	1166	0	0	0	1	0	0
1	512	1007	0	0	0	1	0	0
1	452	972	0	0	0	1	0	0
1	452	811	0	0	0	1	0	0
1	88	1025	0	0	0	1	0	0
1	44	1000	0	0	0	1	0	0
1	44	700	0	0	0	1	0	0
1	181	1763	0	0	0	1	0	0
1	44	423	0	0	0	1	0	0
1	62	409	0	0	0	1	0	0
1	158	112	0	0	0	1	0	0
1	181	167	0	0	0	1	0	0
1	181	184	0	0	0	1	0	0
1	264	289	0	0	0	1	0	0
1	398	298	0	0	0	1	0	0

Presence	Dist to Roads (m)	Dist to Water (m)	Urban, recreational grasses	Low intensity residential	Evergreen forest	Shrubland	Grasses, herbaceous	Emergent, herbaceous wetland
1	316	427	0	0	0	1	0	0
1	378	1015	0	0	0	0	1	0
1	343	1013	0	0	0	0	1	0
1	433	1239	0	0	0	0	1	0
1	88	1642	0	0	0	0	1	0
1	237	2153	0	0	0	0	1	0
1	158	2253	0	0	0	0	1	0
1	44	743	0	0	0	0	1	0
1	256	1225	0	0	0	0	1	0
1	197	1286	0	0	0	0	1	0
1	44	1262	0	0	0	0	1	0
1	158	412	0	0	0	0	1	0
1	44	76	0	0	0	0	1	0
1	44	54	0	0	0	0	1	0
1	132	10	0	0	0	0	1	0
1	158	1103	0	0	0	0	1	0
1	359	289	0	0	0	0	1	0
1	346	251	0	0	0	0	1	0
1	283	157	0	0	0	0	1	0
1	300	188	0	0	0	0	1	0
1	314	430	0	0	0	0	0	1
1	393	367	0	0	0	0	0	1
1	352	384	0	0	0	0	0	1
1	352	380	0	0	0	0	0	1
1	387	351	0	0	0	0	0	1
1	387	358	0	0	0	0	0	1
1	422	332	0	0	0	0	0	1
1	334	379	0	0	0	0	0	1

Presence	Dist to Roads (m)	Dist to Water (m)	Urban, recreational grasses	Low intensity residential	Evergreen forest	Shrubland	Grasses, herbaceous	Emergent, herbaceous wetland
1	268	131	0	0	0	0	0	1
0	352	384	1	0	0	0	0	0
0	346	462	1	0	0	0	0	0
0	254	641	1	0	0	0	0	0
0	205	726	1	0	0	0	0	0
0	0	1104	1	0	0	0	0	0
0	0	395	1	0	0	0	0	0
0	0	445	1	0	0	0	0	0
0	0	340	1	0	0	0	0	0
0	214	812	1	0	0	0	0	0
0	225	885	1	0	0	0	0	0
0	318	552	0	1	0	0	0	0
0	99	1482	0	0	1	0	0	0
0	254	316	0	0	0	1	0	0
0	70	872	0	0	0	1	0	0
0	70	852	0	0	0	1	0	0
0	141	926	0	0	0	1	0	0
0	111	1468	0	0	0	1	0	0
0	99	1571	0	0	0	1	0	0
0	35	1239	0	0	0	1	0	0
0	70	430	0	0	0	1	0	0
0	99	409	0	0	0	1	0	0
0	0	975	0	0	0	1	0	0
0	35	826	0	0	0	1	0	0
0	145	837	0	0	0	1	0	0
0	222	923	0	0	0	1	0	0
0	105	840	0	0	0	1	0	0
0	70	831	0	0	0	1	0	0

Presence	Dist to Roads (m)	Dist to Water (m)	Urban, recreational grasses	Low intensity residential	Evergreen forest	Shrubland	Grasses, herbaceous	Emergent, herbaceous wetland
0	105	614	0	0	0	1	0	0
0	105	498	0	0	0	1	0	0
0	362	1021	0	0	0	1	0	0
0	362	1159	0	0	0	1	0	0
0	222	2084	0	0	0	1	0	0
0	256	1967	0	0	0	1	0	0
0	300	1844	0	0	0	1	0	0
0	35	1709	0	0	0	1	0	0
0	79	2062	0	0	0	1	0	0
0	127	1371	0	0	0	0	1	0
0	35	1540	0	0	0	0	1	0
0	50	1686	0	0	0	0	1	0
0	176	1629	0	0	0	0	1	0
0	298	1294	0	0	0	0	1	0
0	410	1356	0	0	0	0	1	0
0	199	1642	0	0	0	0	1	0
0	176	1744	0	0	0	0	1	0
0	99	1863	0	0	0	0	1	0
0	35	1961	0	0	0	0	1	0
0	99	1989	0	0	0	0	1	0

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