Spatial Distribution of the Endangered Pacific Pocket Mouse (*Perognathus longimembrus* ssp. *pacificus*) Within Coastal Sage Scrub Habitat at Dana Point Headlands Conservation Area

by

Sarah Godfrey

A Thesis Presented to the
Faculty of the USC Graduate School
University of Southern California
In Partial Fulfillment of the
Requirements for the Degree
Master of Science
(Geographic Information Science and Technology)

August 2018

To mom and dad for encouraging me to pursue my passion of conservation as a career, to my friends who have cheered me on through this process, and to Paola, Momo, and Sherman Anderson for supporting me tirelessly.

Table of Contents

List of Figures vi

List of Tables viii

Acknowledgements ix

List of Abbreviations x

Abstract xi

Chapter 1 Introduction 1

1.1. Ecology of the species 1

1.1.1. Monitoring PPM 9

1.1.2. Spatial scale of the study area 10

1.2. The role of GIS and Remote Sensing 19

1.3. Thesis Goals 20

1.4. Thesis Organization 20

Chapter 2 Related Work 22

2.1. Species Distribution Models 22

2.1.1. Ecological Niche Modeling 22

2.1.2. Maxent 23

2.2. Remote Sensing 25

2.2.1. Multispectral Imagery 26

2.2.2. NDVI 28

2.2.3. Panchromatic Bands 29

2.3. Image fusion and Pansharpening 29

Chapter 3 Methods 31

3.1. Data Description 31

3.1.1. PPM presence data 31

3.1.2. Digital Globe Imagery satellite imagery-derived environmental variables 32
3.1.3. Lidar-based environmental variables 39
3.2. Research Design 40
Chapter 4 Results 41
4.1. Image processing results 41
4.1.1. MaxLike Classifications 43
4.2. Maxent Models 45
4.2.1. Preliminary Maxent models 46
4.2.2. Imagery reclassification 46
4.3. Final Maxent models at 10 m spatial resolution 50
4.4. NDVI 58
Chapter 5 Discussion and Conclusions 61
5.1. Model performance 61
5.1.1. Persistent Importance of Distance to Anthropogenic Features 61
5.1.2. Distance to Trail 62
5.1.3. Vegetation types as environmental variables 63
5.2. Vegetation layer importance versus NDVI 64
5.2.1. A case for site selection and field knowledge 65
5.3. Effective Preserve Area and Management Recommendations 65
5.4. Future work 67
References 69
Appendix A 75

List of Figures

Figure 1. Location of CNLM's Dana Point Habitat Conservation Area, Dana Point, CA 2

Figure 2. Historic Range of PPM 3

Figure 3. Current Range of the Pacific Pocket Mouse in San Diego and Orange Counties 4

Figure 4. Grid cell monitoring layout at Dana Point Preserve 7

Figure 5. Spatial Distribution of PPM documented by trapping efforts in 2009 and 2012 8

Figure 6. Differences in scale between landscape ecology and cartography. Source: Timm 2008 11

Figure 7. Modifiable Area Unit Problem for modeling small mammals in a fragmented landscape. Source: Ecke 2003 12

Figure 8. Aerial photo of Dana Point Headlands circa 1925. Source: Dana Point Nature Interpretive Center 14

Figure 9. Aerial photo from late 1990s. Source: Dana Point Nature Interpretive Center 14

Figure 10. Imagery from June 2009, the year that the highest number of individuals of PPM were captured. Source: Google Earth 15

Figure 11. Imagery from October 2016 exhibits visible change in site and peripheral conditions. Source: Google Earth 15

Figure 12. Description of the Multispectral bands of the Digital Globe WorldView-2 Satellite Source: Digital Globe 2009 34

Figure 13. Image Processing Workflow 36

Figure 14. Polygons created for 2010 and 2017 training groups and their spectral signature comparisons 42

Figure 15. Example of lemonadeberry vegetation layer binary classification 47

Figure 16. 0.5 m Lemonadeberry example of spatial resolution after Focal Statistics 47

Figure 17. 10 m Lemonadeberry example of resampled raster 48

Figure 18. Distance to anthropogenic features at 0.5 m and 10 m resolutions 48

Figure 19. Distance to trail raster at 0.5 m and 10 m spatial resolution 49

Figure 20. 10 m spatial resolution DEM 49

Figure 21. Contributions of environmental variables compared by importance in the model (left) and independently (right) with PPM presence 55

Figure 22. Receiver Operating Characteristic of top performing Maxent model 56

Figure 23. Omission rates for top performing Maxent model 57

Figure 24. Point-wise mean (average) of points in the model with 2009 presence locations 57

Figure 25. NDVI results for 2010 pansharpened imagery at 0.5 m resolution 59

Figure 26. NDVI of 2017 imagery 60

Figure 27. NDVI Overlay showing change in plant vigor between 2010 and 2017 60

List of Tables

Table 1. Pacific Pocket Mouse monitoring efforts at Dana Point Preserve from 1992–2017........ 5

Table 2. Field vegetation survey results from five transects across Preserve.............................. 16

Table 3. Rainfall from 2008–2017.. 18

Table 4. Comparison of resolution between common available satellite imagery 32

Table 5. Probability of likelihood assigned to each training category for MaxLike classifier for 2010 and 2017 imagery... 37

Table 6. Classification results for 2010 imagery 43

Table 7. Class percentages and frequency for 2017 classification 44

Table 8. Differences between classifications in 2010 and 2017 imagery using classified imagery with 200 m Preserve Boundary buffer 45

Table 9. Percent change in counts using classified imagery clipped to Preserve boundary......... 45

Table 10. Sample of results using various input variables and Maxent settings 52

Table 11. Highest performing model variables' percent contribution and permutation importance 52

Table 12. Percentage of histogram values in distinct ranges... 59

Acknowledgements

I am grateful to the faculty at USC for providing me a solid background in GIS and for opening my mind to new opportunities of thinking geospatially. Dr. Travis Longcore was an incredible mentor in guiding me through this process of geospatial ecological analysis, and it was an honor to work with him. My committee members, Col. Steven Fleming and Dr. Laura Loyola, contributed to my success with their expertise, editing, and humor, and I appreciate Dr. Karen Kemp's dedicated engagement in the development of this project. This thesis is dedicated to Richard Holden Godfrey, Sr., for instilling a legacy of environmental ethic in his family and community, and for his commitment to conservation of place.

List of Abbreviations

CESA	California Endangered Species Act
CNLM	Center for Natural Lands Management
CSS	Coastal Sage Scrub
DEM	Digital Elevation Model
ENM	Environmental Niche Models
ESA	Endangered Species Act
GIS	Geographic Information System
GLM	Generalized Linear Model
HCA	Habitat Conservation Area
HSM	Habitat Suitability Models
MAUP	Modifiable Areal Unit Problem
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
PPM	Pacific Pocket Mouse
RS	Remote Sensing
SDM	Species Distribution Model
USFWS	United States Fish and Wildlife Service

Abstract

Understanding spatial and temporal change in distribution of endangered species within urban, fragmented landscapes has increased as an area of ecological study in the last fifty years in concert with improvement of environmental protection regulations. This research involves designing a species distribution model for Pacific pocket mouse (*Perognathus longimembrus pacificus*; PPM) to generate predictions about their habitat use. The main goal was to understand the relationship between distinct occurrence locations and environmental variables within a 0.12-km^2 Habitat Conservation Area in May 2009 for later spatio-temporal comparison. Environmental variable layers were generated using supervised classification of Digital Globe's WorldView-2 high-resolution satellite imagery, in addition to other vegetation health measures and topography. A model was developed using the open source software program Maxent to spatially represent the distribution of PPM and the variables that may have influenced their presence. Results indicated that distance to houses and anthropogenic infrastructure strongly influences PPM distribution. Proximity to California sagebrush (*Artemisia californica*) and buckwheat (*Eriogonum fasciculatum*) show a positive relationship with PPM occurrence. Another strong positive influence on PPM presence was proximity to a recreational trail, which indicates that a level of moderate disturbance may benefit the species. This thesis presents the idea that appropriate habitat disturbance may be necessary to improve the spatial distribution of the PPM, and suggests ideas for further research to enhance understanding of human and environmental impacts to the species.

Chapter 1 Introduction

Pacific pocket mouse (*Perognathus longimembrus* ssp. *pacificus*; PPM) is a charismatic species whose persistence within a specific habitat structure and composition of limited range presents an opportunity to study a fine grain area using remote sensing and GIS.

1.1. Ecology of the species

Pacific pocket mouse is a nocturnal rodent, a member of the Heteromyidae family, and the smallest subspecies of the little pocket mouse (Brylski 1998). Its native range once extended from coastal Los Angeles County to San Diego County and it had not been observed in any locale since 1971 (Federal Register 1994) until it was incidentally discovered in 1993 during a survey on the Dana Point Headlands by Dr. Phil Brylski. The species was emergency-listed as a federally endangered species in 1994, with an assumed minimum of 36 individuals occupying 3.75 acres (15,175 m^2) at that time (Federal Register 1994). The property on which it was found was eventually set aside in perpetuity as a Habitat Conservation Area (HCA; Preserve) (Figure 1) which is managed by the Center for Natural Lands Management (CNLM), which employs the author of this thesis. A Recovery Plan for the species was released in 1998 by the US Fish and Wildlife Service (USFWS), with specific goals and measures to prevent the species' extinction (Brylski 1998). Researchers have documented the distribution and abundance of PPM through trapping with modified Sherman traps and through "track tubes" that capture rodent footprints using baited cards with ink pads on either end. Habitat conditions have been monitored at trap locations using transects to record vegetation health and composition, and quantitative monitoring methods have been used to inform vegetative management. The presence of predators and possible competition for resources has been documented using two motion-sensing wildlife cameras and by conducting surveys for the Argentine Ant (*Linepithema humile*; LIHU).

These combined monitoring efforts have contributed to a comprehensive understanding of the ecology of the Preserve and the persistence of the PPM since they were rediscovered in 1993. However, questions remain about what habitat conditions most influence its distribution.

Figure 1. Location of CNLM's Dana Point Habitat Conservation Area, Dana Point, CA

The historic distribution of the PPM was coastal dune, alluvium, and coastal sage scrub (CSS) habitat with bare, sandy soils within approximately 2 miles of the coast. According to Dr. Brylski, PPM on the Preserve prefer "open coastal sage scrub on fine, sandy soil" (Federal Register 1994). Species records before 1971 exist from as far north as Marina del Rey, Los

Angeles County, to the southernmost record from lower Tijuana River in San Diego County (Figure 2). Currently, there are only three known populations of PPM, which are on the Preserve, and in two locations on Marine Corps Base Camp Pendleton (MCBCP), approximately nine miles and 25 miles to the south of the Dana Point population (Figure 3). All known populations are being actively monitored by the United States Geological Survey (USGS) and CNLM in conjunction with the USFWS, and a captive breeding program using individuals from all populations is being operated by the San Diego Zoo with the USFWS.

Figure 2. Historic Range of PPM

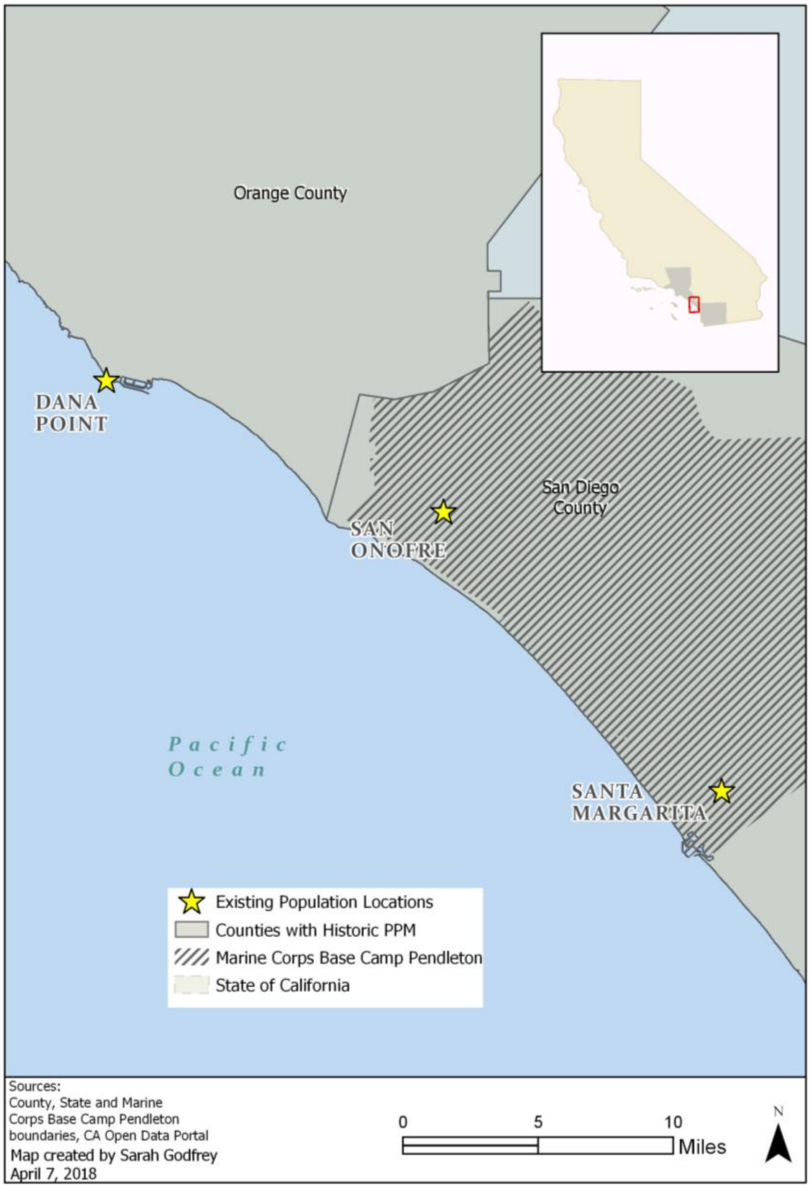

Figure 3. Current Range of the Pacific Pocket Mouse in San Diego and Orange Counties

Ongoing surveys at the Preserve have been important for capturing general information regarding site occupancy, detecting large changes in population size and distribution, and estimating total area occupied. Trapping efforts are measured by the number of trap nights, which is the number of checks per night multiplied by the number of nights by the number of trap locations. The number of PPM counted has varied widely over time, but the most notable surveys occurred when eighty-two (82) unique individual mice were captured in 2009, fifty-seven (57) mice were captured in 2012, and only six (6) were captured in 2017 (Table 1).

Table 1. Pacific Pocket Mouse monitoring efforts at Dana Point Preserve from 1992–2017

Year	Monitoring Type (area if other than full Preserve)	Result #PPM or Proportion Area Occupied	# Trapping Nights	Dates
1992–1993	Traps (3.5 ac)	25, 36	817, 648	July 19–Aug 5
1995–1996	Traps (3.75 ac)	8	815	Aug 28–Sept 6
1996–1997	Traps & traplines (7.55 ac)	21	2,782	Aug 19–28
1997–1998	Traps & traplines (7.55 ac)	19	3,325	July 24–Aug 4
1998–1999	Traps	11	3710	April 28–May 5
1999–2000	Traps	6	3080	May 5–11
2000–2001	Traps	4	4835	May 30–June 5
2001–2002	Traps	2, 0	2916, 3035	Aug 5–13, Aug 18–Sept 1
2006–2007	Traps (along trail)	1	925	April 12–20
2007–2008	Traps	30	3280	May 2–7, June 6–11
2008–2009	Traps	82	3362	May 1–11
2010–2011	Track Tubes	36% south of road, 59% north of road (29.4ac)	7,088	N/A
2011–2012	Traps	57	3,330	May 1–11
2012–2013	Track Tubes	51.6% (29.4ac)	378	May 2–17
2013–2014	Track Tubes	80.7% (29.4ac)	1890	April 25–May 7
2015–2016	Track Tubes	70.7% (29.4ac)	4030	April 8–May 10
2016–2017	Traps	6	1143	May 21–24

Sources: Miller 2018 and CNLM 2018

Though this may appear to be a dramatic decline between 2009 and 2017, the track tube studies, which have been conducted in the interim years, have demonstrated site occupancy as high as 81% in 2013 and as low as 36% in 2011 (CNLM 2014). Small mammals are susceptible to extreme population fluctuations (Kim, Tschirhart, and Buskirk 2007) and a variety of factors may have contributed to the low numbers observed in 2017. Rodent populations often exhibit temporal and spatial variability in arid environments (Thibault et al. 2010). It has been suggested that PPM populations generally do well in years of drought and low rainfall, because their competitors may dwindle as resources become low (Shauna King, pers. comm. February 22, 2018). Years of heavy rainfall and abundant resources may cause the population to respond negatively as competitors (i.e. woodrats, *Neotoma* spp.) increases. Additionally, the observed response to precipitation may be confounded by a shift in species composition (increased number of deer mouse, harvest mouse, or woodrat), shifts in rain events (drought followed by above average precipitation), and a change in vegetation community (mature coastal sage scrub) (Thibault et al. 2010).

The monitoring efforts have been conducted using different methodologies depending on the purpose of the survey (i.e. population assessment or proportion area occupied), adaptive management, efforts to have least impacts to the species, and cost effectiveness for the Preserve. Live trapping efforts were used primarily for population assessment and proportion area occupied measurements, in addition to captures for the captive breeding project, while track tube monitoring was for PPM activity monitoring and proportion area used estimates. Distinctly different methods of trap placement and study design complicates the interpretation of data. As trapping efforts evolved, intervals of 3 m, 5 m, 8 m, and 10 m spacing were tested, as well as strategic population monitoring using 24 m x 24 m grid cells across the 29.4-acre (~.12 km^2) site (CNLM 2016). In 2009, in accordance with the preceding year, a 16 m x 16 m grid with 96 individual cells was overlaid on the Preserve south/west of Old Marguerita Road, and small mammal trapping was performed within the same 64 grid cells that were randomly selected for sampling in 2008. A square 3 m x 3 m array of Sherman live traps (nine traps total) was placed in the center of each cell. This provided a separation of four meters between outer trap lines and the boundary of each grid cell, and a minimum separation of eight meters between trap stations placed in adjoining cells (Figure 4).

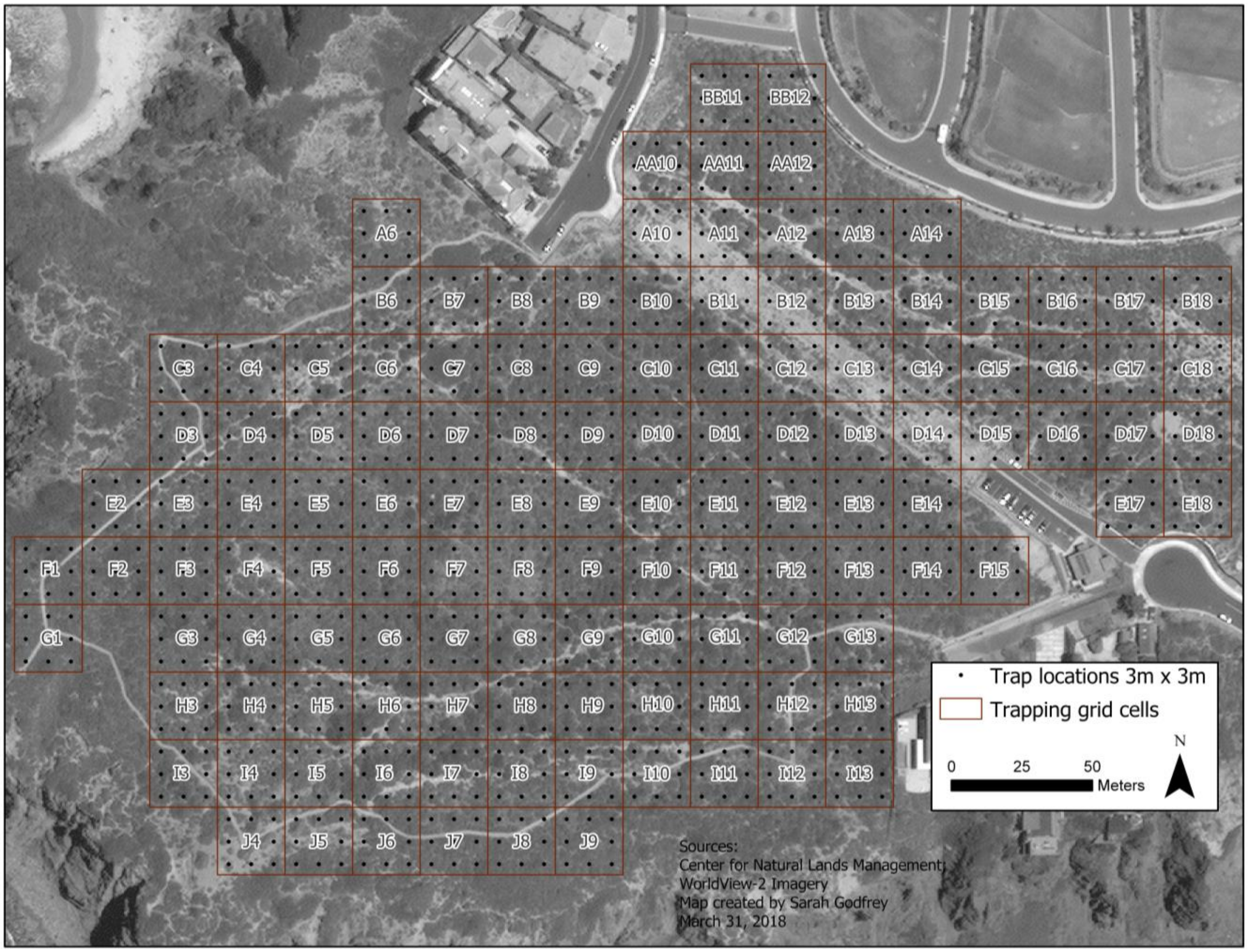

Figure 4. Grid cell monitoring layout at Dana Point Preserve

Between the 2009 and 2017 surveys, two noticeable differences were the number of traps set and the spacing between them; the former used 8-m spacing between grid cells and the latter were 24 m apart, and the trap nights were abbreviated in 2017 due to high mortality of wood rats in the modified Sherman traps. The 2017 trapping efforts repeated those used in 2012, where the entire Preserve was sampled with three live-traps (a modified 9-inch Sherman trap) placed within 5 to 8 m of the center of each grid cell. The spatial distribution of the PPM in 2017 showed the mice occupying areas which were part of the habitat restoration nearest to the Old Marguerita

Road, whereas they were evenly distributed around the southern portion of the Preserve in 2012 (Figure 5).

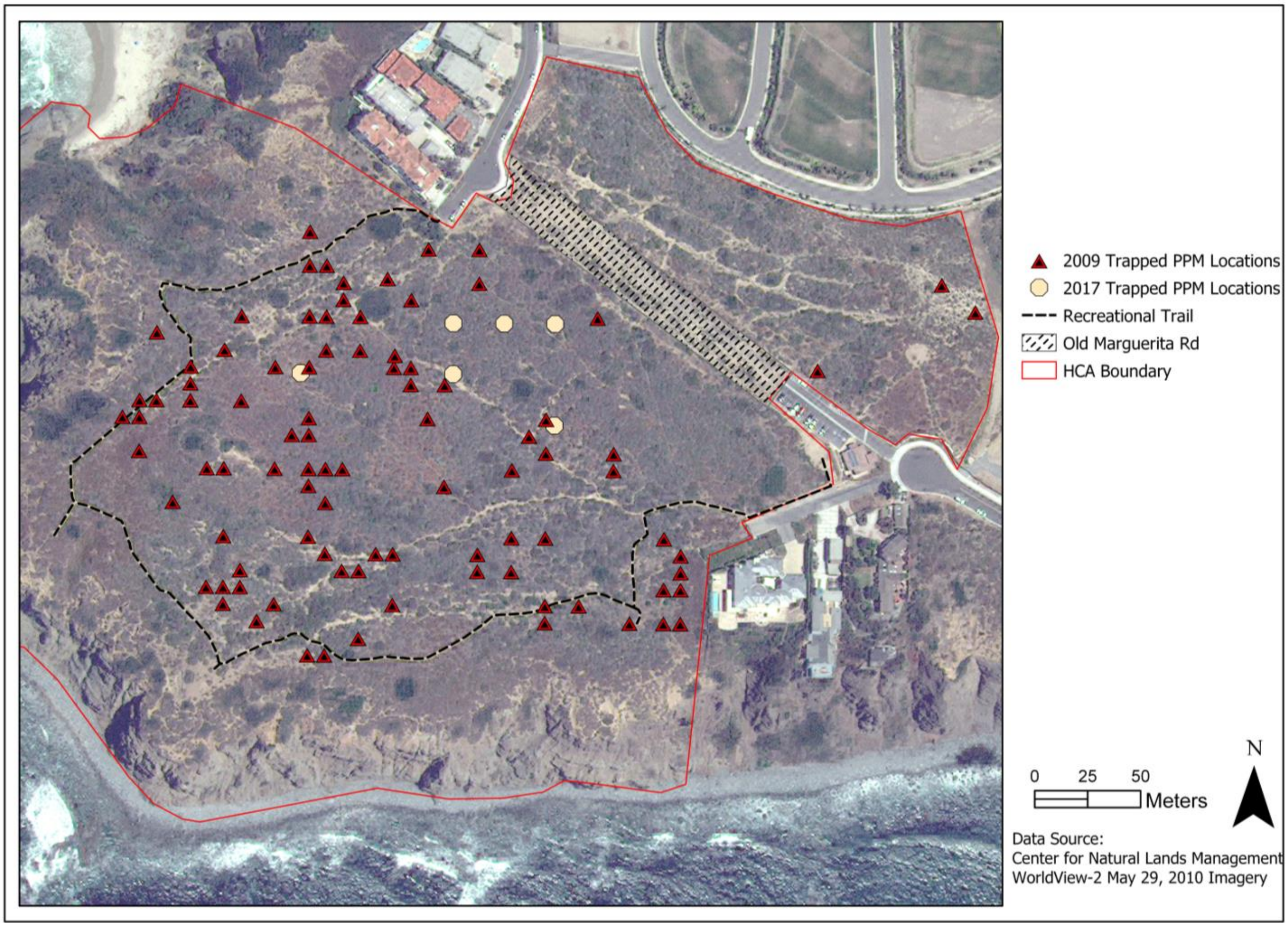

Figure 5. Spatial Distribution of PPM documented by trapping efforts in 2009 and 2012

Modeling has been performed to study the movement distance and discovered 10–30 m recaptures (Brehme et al 2014; Dodd et al 1998). They approached multiscale plots to address the dynamics of the PPM at different spatial scales in response to change in habitat and disturbances. Habitat modeling included topography, soil, vegetation cover, and proportion area occupied by PPM, and a main conclusion was that detection of spatial density of other animals was one of the best predictors of PPM (Brehme et al 2014).

1.1.1. Monitoring PPM

PPM is a cryptic, nocturnal creature that lives below ground and is primarily only active above-ground from February to October during foraging and mating activities (Brehme et al. 2014). It is difficult to detect with surveys, because it is susceptible to being outcompeted by other species and the sampling is time-consuming and expensive. During trapping efforts, unique individuals were still being detected after 20 days (Markus Spiegelberg, pers. comm., April 11, 2018), which is highly unusual. If there are other species around the site which could take the bait from the track cards or traps, the PPM cannot compete and do not express themselves (Brehme et al. 2014). Furthermore, as a small stature, localized species that is very rare, it is inherently cryptic, which makes it harder to detect (Schaffer-Smith, Swenson, and Penalba 2016). Many analyses have been performed to study distance traveled by the species (Dodd et al 2009), correlating the presence and/or proportion area occupied to vegetation using transects and linear regression (CNLM 2014), as well as other factors which may affect the species movement such as presence of duff and leaf litter (CNLM 2014).

As previously mentioned, the two main methods of monitoring the PPM have been capturing the animals in Sherman modified traps and detecting them in track tube surveys. The track tube surveys are a more cost-efficient way of studying the distribution of PPM, however, they do not indicate population size or track individuals. Biologists determined how far an individual will travel to obtain food with the trapping method, and established a best fit 24 m x 24 m grid to monitor the species based on that distance (CNLM 2008). Since 2008, the study area has been defined by these grid cells with an alphanumeric code in which presence or absence has been recorded. Although comparison between years and monitoring types (track tube versus live traps) on the Preserve is limited due to differences in trapping effort and seasonality, monitoring efforts on the Preserve do show temporal fluctuation since trapping began in 1992. Whether these fluctuations are due to precipitation, competition, human presence or PPM growth rate is unknown. The complexities of the influence of precipitation on small mammal communities in arid environments are difficult to separate from other factors, and more research is needed to make a decisive conclusion on what is influencing populations temporally and spatially (Thibault et al. 2010).

1.1.2. Spatial scale of the study area

The large spatial scale (fine grain) of the study site presents unique challenges to understanding trends and determining an appropriate method of analysis, which is another well-studied topic in conservation (Levin 1992). The Preserve is such a small area and surrounded by developed area to the north and east, and a steep bluff edge to the ocean to the south and west. Therefore, it can be analyzed as an island due to its strong influence by external pressures, limited capacity for occupancy, as well as restricted animal movement in and out of the Preserve.

The issues of scale and grain in ecology and geospatial/cartographic analysis are somewhat contradictory in the language used to describe an area, with a fine scale in the former meaning a large scale in the latter (Timm 2008; Figure 6). Timm studied Southern California’s coastal sage scrub at multiple scales to determine the spatial and temporal resolutions that were meaningful to detect change, and presented this in her work for the Natural Reserves of Orange County.

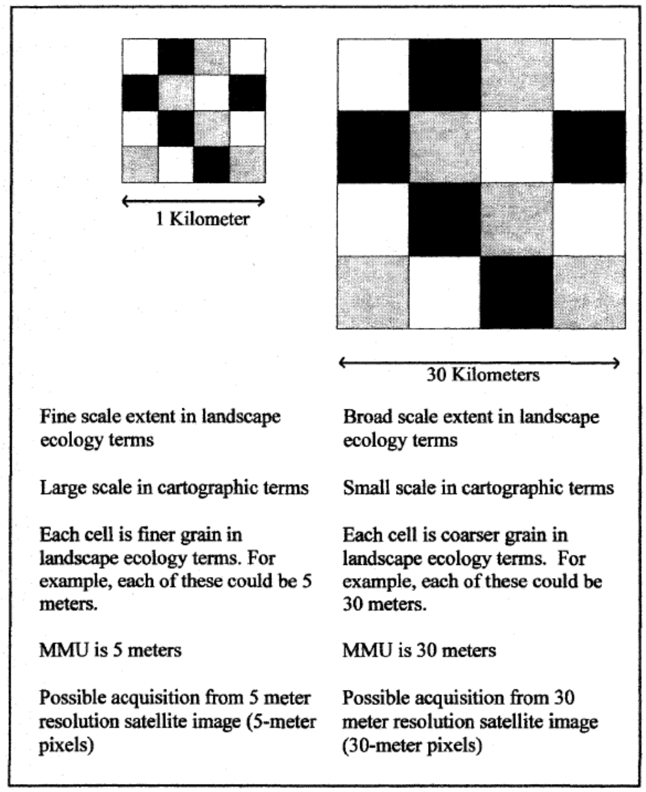

Figure 6. Differences in scale between landscape ecology and cartography. Source: Timm 2008

As the overall health, composition, and function of this ecosystem can be detected in many grains, it is important to create a scalable model and acquire datasets for multiple analysis performance. The idea of designing an appropriate study scale and measure of population across an area can be considered the modifiable area unit problem (MAUP) (Dark and Bram 2007). The MAUP is important to capturing the trends on site, thinking beyond the 24 x 24 m grid cell and more about the overall trends in available and occupied truly suitable habitat. Scale and the MAUP were important considerations in choosing appropriate spatial resolution for the environmental variable inputs which were created for Maxent in this study. Ecke (2003) examined the challenges of modeling small mammals on the landscape to correlate factors of density with site variables using Fragstats, demonstrating ways of looking at such populations (Figure 7).

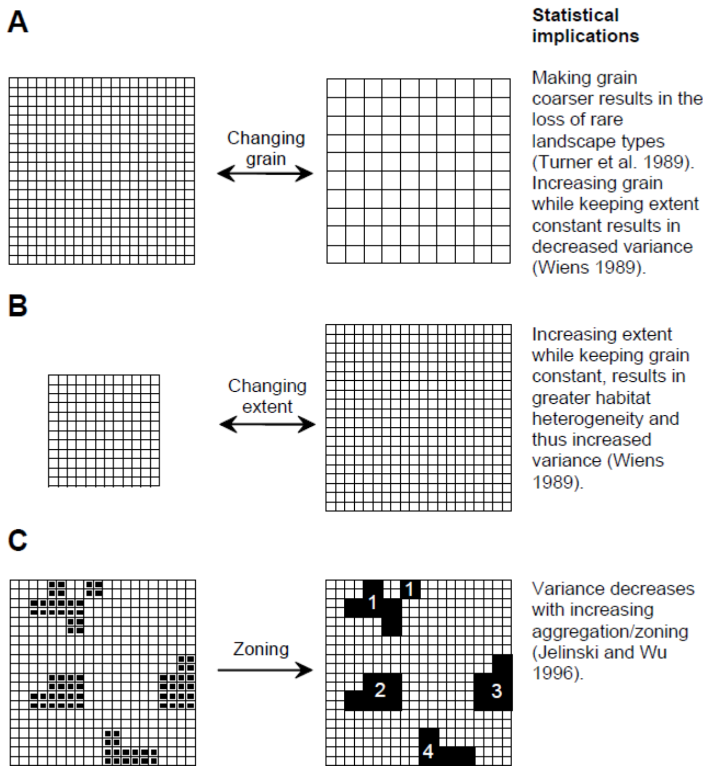

Figure 7. Modifiable Area Unit Problem for modeling small mammals in a fragmented landscape. Source: Ecke 2003

Choosing a minimum mapping unit (MMU) that incorporates the spatial resolution needed to include all the site's fine detail yet coarse enough to capture the placement area of the trap can be consistently expanded upon. Thinking through these spatial questions supports an approach to using a species distribution model that yields an understanding of the habitat needs of rare and endangered species when overall population and distribution is low. Additionally, defining a measure on large spatial scale can be repeated in future applications for the greater population distribution.

1.1.2.1. Coastal Sage Scrub Habitat

Coastal sage scrub habitat is a priority habitat in Southern California because so little acreage of this assemblage remains intact, and there are endangered species that rely on its vegetation structure and composition for persistence (O'Leary 1990). Although the USFWS has not designated it as critical habitat for the PPM (USFWS 1994), coastal sage scrub is conserved for the coastal California gnatcatcher (*Polioptila californica californica*), which is another endangered species that resides on the Preserve. The characteristic California sagebrush (*Artemisia californica*) and bush sunflower (*Encelia californica*) are drought-deciduous and prone to long periods of dormancy during the hot, dry summer months (approximately June–October) until rain stimulates growth. For this reason, it is important to study vegetation during the peak of its cycle to capture its optimal vigor (Dennison and Roberts 2003a).

Dana Point is a bustling harbor town with a rich history in Orange County, Southern California, where urban development has accelerated on much of the coastal area since the dedication of the harbor in 1961 (Renee Cortez, pers. comm., March 1, 2018). The Headlands has been a beloved part of the city's history for generations, experiencing its first subdivision in 1925, and providing ongoing active recreation (including motor vehicles, partiers, and dog walkers) until it was fenced as a PPM Preserve (Renee Cortez, pers. comm., March 1, 2018). Evidence of its extensive use can be observed in aerial photography from the prior to the time of the rediscovery of the PPM, and reviewing aerial photos reveals interesting ideas about changes in the immediate landscape surrounding the Preserve (Figures 8–11).

Figure 8. Aerial photo of Dana Point Headlands circa 1925. Source: Dana Point Nature Interpretive Center

Figure 9. Aerial photo from late 1990s. Source: Dana Point Nature Interpretive Center

Figure 10. Imagery from June 2009, the year that the highest number of individuals of PPM were captured. Source: Google Earth

Figure 11. Imagery from October 2016 exhibits visible change in site and peripheral conditions. Source: Google Earth

Upon establishment of the PPM Preserve, which was designated with funding from a grant from the Steele Foundation, recreation became limited to a California Coastal Commission-designated trail from the two adjacent streets around the perimeter. Vegetation within the Preserve could mature within the boundaries and provide habitat for the endangered gnatcatcher as well as the PPM. Habitat restoration on the Old Marguerita Road expanded native plant habitat consisting of sagebrush and sunflower. The vegetation on the Preserve was monitored regularly to inform management using five transects which were randomly stratified across the habitat and intersecting PPM monitoring locations. Values of percent live and dead vegetation, as well as ground cover and bare ground were recorded for quantitative comparison between years (Table 2).

Table 2. Field vegetation survey results from five transects across Preserve

Year	***Vegetation surveys***	***Mean % Cover Live***	***Mean % Cover Dead***	***Mean % Ground Cover (Litter)***	***Mean % Ground Cover (Bare Ground)***
2008–09	Yes	51.00	24.80	72.00	27.20
2009–10	No				
2010–11	No				
2011–12	Yes	77.00	13.00	N/A	N/A
2012–13	Yes	68.40	16.80	73.20	24.80
2013–14	Yes	76.80	18.40	76.40	20.00
2014–15	No				
2015–16	Yes	21.5	33.2	32.4	22
2016–17	No				

Source: CNLM 2018

One of the hypotheses about PPM distribution is that they are associated with areas of lower vegetation cover and exposed soil/sand, and occur less frequently or are absent in areas with high vegetation cover (CNLM 2014). The vegetation surveys and land manager observations documented accumulation of leaf litter, woody debris, and other organic material, collectively referred to as duff, building up over time under and around the coastal sage scrub vegetation. This has led to the hypothesis that accumulated duff on the ground surface in addition to high vegetation cover is reducing the availability of bare soil, thus inhibiting germination of native forb species for forage, and degrading habitat quality for PPM burrows. To test this as part of its adaptive management of the Dana Point Preserve, CNLM implemented a duff removal experiment in 2008 to see if removing duff can improve habitat conditions for PPM. Duff was removed in grid cells where no PPM had been documented, and a regression analysis was performed on the following years' captures to test the theory. There was no statistical significance between grid cells where duff had been removed and those that had not been treated. However, land managers have continued to selectively remove duff and dead shrubs to maintain openings and create optimal forage and burrow space for the PPM.

A major drought, certain to have affected the growth rate and mortality of the vegetation at the Preserve, struck Southern California (USGS 2017) between 2011 and 2017 (Table 3). Though it has adapted to withstand dry periods, coastal sage scrub is dependent on a Mediterranean climate with winter rains, as opposed to a semi-arid desert-like absence of rain. The average rainfall at Dana Point is 12.8 inches per year, or approximately 8.67 inches during the active growing season between October and May (Weather Underground). Rainfall in the temporal period of the growing season is important to consider because it influences coastal sage scrub peak growth and vigor.

Table 3. Rainfall from 2008–2017

Year	***Total Rainfall (inches)***	***Percent (%) of Average Rainfall (12.8)***
2008–2009	8.42*	65
2009–2010	9.34	73
2010–2011	11.95	93
2011–2012	4.64	36
2012–2013	4.88	38
2013–2014	2.7	21
2014–2015	3.05	24
2015–2016	4.43	35
2016–2017	10.92	85

Source: Weather Underground with all data from Strands Beach Weather Station except *Irvine CIMIS Station

The vegetation on the Preserve arguably has been impacted by the ongoing drought, however, there are many other influencing factors to habitat quality. Another factor to consider is the composition of single-age vegetation which has experienced a decline in disturbance since Preserve establishment and is limited in new recruitment of shrub seedlings and annual forbs. It is possible, as in the case of several butterfly species that have experienced declines following establishment of preserves areas (Longcore and Osborne 2015, Longcore et al. 2010), that more extensive disturbance is necessary for the PPM. The PPM population that persists in highest numbers at Camp Pendleton is in a regular artillery fire area, and generally habitat disturbance is a high contributor to rodent species distribution (Ceradini and Chalfoun 2017). Suggestions have been made to reintroduce fire to Dana Point Preserve and to continue vegetation removal as simulated mechanisms of disturbance (Korie Merrill, pers. comm., February 23, 2018). By understanding how the PPM distribution has changed as vegetation and bare ground percentages fluctuate, we can help to inform management strategies for the extant population and the release of captive-bred individuals.

1.1.2.2. A changing landscape

Landscape fragmentation is a long-studied topic in conservation biology and landscape ecology, as is designing appropriate habitat requirements and corridors to support persistence of a species. Important questions can be asked: 1) How much critical habitat is sufficient to support a population? 2) Will the habitat be appropriate to support the existing and future populations without causing genetic depression in the face of isolation (Lande 1995)? 3) Is the total Preserve area serving as effective habitat for the species at risk?

Factors which may be of influence on the Preserve have been discussed, however the external pressures that contribute to the Preserve's species richness cannot be dismissed. Over the last thirty years since Dana Point was incorporated as its own city, there has been a tremendous increase in traffic along Highway One, which is just east of the Preserve. There has been ongoing ground disturbance associated with the creation of the Strand at Headlands housing development to the north. The housing contributes street lighting to the Preserve, introduces potential for domestic cats to prey on Preserve species, and inhibits predators such as bobcat and coyote from controlling species which are competitive to PPM resources due to the combination of traffic and human presence. The factor which is most quantifiable, distance to anthropogenic features, will be evaluated in this analysis.

1.2. The role of GIS and Remote Sensing

GIS and remote sensing (RS) can help to demonstrate the temporal and spatial changes of plant species distribution and habitat composition which support the PPM; measurable differences in percent living and dead vegetation, leaf litter known as "duff", and adjacent land use may be correlated to the detected animal populations. In the Dana Point population, the species is thought to prefer open, sandy soil with 30% vegetation cover of coastal sage scrub habitat as the open bare ground is necessary for growth of herbaceous plants that serve as fodder for the animals, and allows them space to create the large underground burrows in which they live (USFWS 1998). In 1993, when PPM were rediscovered, the terrain was heavily disturbed and with sparse vegetation. Even in 2009 when there was a robust population of individual PPM, there was a high amount of bare ground and healthy vegetation throughout the Preserve and especially in the newly restored habitat on the Old Marguerita Road. GIS and RS were used to take an analytical view beyond visual interpretation to understand the site change phenomena.

1.3. Thesis Goals

The goal of this thesis is to determine where suitable habitat exists at the Preserve at the point of highest numbers of PPM and to understand what environmental variables have the greatest influence on PPM distribution. The primary objective is to create a repeatable method of image analysis that can evaluate environmental conditions in the coastal sage scrub habitat, and be successfully integrated with species presence information using maximum entropy modeling of the species' environmental niche. An analysis of the vigor of plants, evaluating the change in percent cover of living vegetation and bare ground, as well as the percent cover of bare ground, was an expository way of demonstrating possible impacts to PPM. This evaluation was accomplished using multispectral analysis techniques including NDVI and supervised classification of high-resolution satellite imagery with the panchromatic band. Environmental raster data was prepared for comparison of species observation locations; reclassification, visual analysis and polygon digitizing was used in conjunction with the image extraction processes.

1.4. Thesis Organization

The next chapter summarizes related work and starts by exploring techniques which have previously been used to map vegetation in the unique coastal sage scrub ecosystem. The chapter provides a background on species distribution modeling techniques and justifies the use of the Maxent program which was selected to identify suitable PPM habitat based on where presence was detected. It also provides robust information on the remote sensing processes which have been used to detect change. Chapter 3 describes the methods used in this study as well as the data used. Chapter 4 details the results for this study, and the final chapter offers a discussion of the broader significance of these results as well as some suggestions for future research.

Chapter 2 Related Work

This chapter describes the applied methods for using remotely sensed satellite imagery to understand changes in vegetation composition, as well as various species distribution modeling approaches that have been proposed and the ways in which they have been used. The Maxent model (Phillips and Dudik 2008) is described in detail as it was used in this study.

2.1. Species Distribution Models

2.1.1. Ecological Niche Modeling

To study landscape trends in a species effectively, multiple approaches have been developed over the years to use GIS for spatial modeling and predictive modeling; these include using a presence-absence (Elith and Leathwick 2009; Irl and Beierkuhnlein 2011), presence only (Smolek 2015), site suitability (Miller, Webster and Stewart 2013; Gaston et al 2017), habitat-association modeling (Fielding and Bell 1997) and other analyses of distribution. These are combined with machine-learning algorithms such as generalized linear models (GLM) which have effectively been used to correlate presence-absence and count data with external environmental factors (Mu et al 2013).

Species distribution models (SDM) and habitat suitability models (HSM) have been used to evaluate habitat of known populations as well as to predict where suitable habitat might exist outside those areas. SDM are numerical tools that combine observations of species occurrence or abundance with environmental estimates of external variables. Species modeling, or environmental niche modeling (ENM) are most often used in one or more of four ways: (1) to estimate the relative suitability of habitat that is known to be occupied by a specific species; (2) to estimate the relative suitability of habitat in a certain geographic region occupied by a species;

(3) to estimate changes in the suitability of a specific habitat over an identified time period; and 4) to estimate the species' niche (Warren and Seifert 2011).

Before an SDM can be developed, one must choose a presence-only data or presence-absence approach to analyzing the data. Presence-only data requires an environmental niche factor analysis (ENFA) whereas GLM are most appropriate given both presence and absence data. Engler, Guisan, and Rechsteiner (2004) and Cianfrani et al. (2013) simulated absence data (called pseudo-absence) to test the effectiveness and choice method for creating a model given presence data, and studies have compared the effectiveness of each in certain scenarios. ENFA quantifies the species' ecological niche by comparing the environmental characteristics of the sites it occupies with the environmental characteristics of the whole study area. The type of data which has been collected as well as the scale at which the environmental information was collected contribute to determining the best model to choose.

2.1.2. Maxent

The maximum entropy (Maxent) modeling method is a powerful tool that determines the relationship between species observations and environmental variables, and is most often used to determine density distribution of species and percent of suitable habitat occupied or available (Philips, Anderson and Schapire 2006). This method has been proven to be the most useful when dealing with known small populations of rare and endangered species (Hernandez et al 2006; Elith and Leathwick 2009). Small sample sizes pose a challenge to any statistical analyses and result in decreased predictive potential when compared to models developed with a greater number of species occurrences. Therefore, it is important to utilize a program that can accurately predict distribution within an area. Hernandez et al. (2006) evaluated eighteen rare species using four modeling programs and found that Maxent could incorporate between five and fifty occurrence locations with high precision, whereas others could not. It performs exceptionally to compare background data with observed presences and predicted presences (Merow, Smith and Silander 2013), which is a key component of this study.

The most important considerations in using Maxent are selecting appropriate environmental covariates, addressing sample bias, and determining the settings for best model fitting, because these significantly affect whether or not the model is ecologically realistic (Guevera et al. 2018). Many of the settings in the Maxent model have been optimized in the program updates to minimize overfitting data (Philips et al. 2017; Philips and Dudik 2008), including the Cloglog, Hinge Features, and multiplier regularizer. Elith et al (2011) exposed a variety of ways that manipulating these settings changed the outputs. In Maxent, model calibration is critical, and the output depends on its complexity, meaning that the accuracy and number of input environmental variables is important. To prevent overfitting, the regularization multiplier setting can be manipulated to fit the scale of the project. Radosavljevic (2014) tested different multipliers and determined that a setting of two (2) was helpful to prevent overfitting some variables. However, Philips et al (2017) describe that they have revised the program so that these multipliers are less needed.

There are multiple ways of evaluating criteria in the Maxent model. The jackknife function, Area Under Curve (AUC), Receiver Operating Characteristics (ROC), permutation importance, percent contribution, and response curve graphs supplement the graphic distribution models produced as outputs. AUC and ROC are used in classification analysis to determine which of the models predicts the classes best, producing curves that plot true positive occurrences against false positive rates. Constant tuning or smoothing model for presence background evaluations, AUC quantifies the probability that the model correctly orders (ranks) a random presence locality higher than a random background pixel (Philips et al. 2006). AUC values calculated with presence background evaluation data vary according to the proportion of the study region that is suitable for the species and, hence, are not comparable among species or across study regions. A value of 0.5 indicates that the model performance is no better than random, while values that are closer to 1.0 indicate better model performance. The magnitude of the difference between calibration and evaluation AUC quantifies the degree of overfitting to noise.

Permutation importance is the contribution for each variable as it is determined by randomly permuting the presence and background training points as well as measuring the resultant decrease in training AUC. The percent contribution values are calculated during model development from changes in the gain while the permutation importance is calculated by having each variable's values changed at the training and background locations and then re-evaluating the model. The marginal response curve graphic outputs demonstrate positive and negative associations, and how the logistic prediction changes as each environmental variable is varied. Proximity of correlation is one measure of the combined effects of the variables, and suitability can be compared between the two plots. The first set of plots represents the change in each variable with all others held constant, and the second set shows the scenario if a model were run using only the charted variable.

2.2. Remote Sensing

Remote sensing (RS) was an important component of creating the environmental variable layers that were integrated into the Maxent model. RS has been used in many studies to detect changes in vegetation composition, even more specifically in the coastal sage scrub habitat. Early research by Davis, Stine and Stoms (1994) pioneered interest in creating vegetation maps of the coastal sage scrub composition and distribution by combining Geographic Information Science (GIS) and RS. Since then, methods for distinguishing individual species, as well as health, vigor, and structure, have been established and tested.

2.2.1. Multispectral Imagery

Many studies have taken advantage of the benefits of high temporal resolution and multispectral properties of satellite imagery. Davis, Stine and Stoms (1994) combined red, near infrared (NIR), and mid-infrared (MIR) bands to create a false color composite map to distinguish vegetation types; they digitized the polygons and field verified the information to confirm its accuracy. Their conclusion was that a finer spatial grain would be more informative, which gives support to this thesis which evaluates CSS health and composition in a small geographic area. The minimum mapping unit (MMU) is another way to set scale in vegetation mapping, where all features smaller than the designated MMU are generalized as a percent cover, and the dominant species are represented. Gaston et al. (2017) compared multi-scale models to determine the differences in model outputs between environmental variable vegetation layers created from 25-hectare MMU, 2.25-hectare MMU, and 0.5 m MMU. They found that the most accurate predictions of brown bear habitat were derived from the highest resolution input imagery.

Landsat ETM imagery and Spot 5 have been commonly used in conjunction with GIS to compare vegetation conditions across seasons and time, create potential habitat maps, and perform NDVI. This imagery is integrated with GIS and GPS data in some form, and validation is performed with a minimum consideration of producer’s accuracy, user’s accuracy, and overall accuracy. Mu et al. (2013) integrated SPOT 5 3S technology and combined multivariate statistical methods with it for habitat mapping, producing suitability maps for a small mammal in

Taiwan. The authors concluded that Spot 5 is not often sufficient alone because it lacks the resolution needed for high quality assessment though they were able to generate meaningful results using Maxent and environmental incidence data with GIS.

Other high-resolution imagery, such as Airborne Visible Infrared Imaging Spectrometer (AVIRIS), has been used to detect change in CSS. Plant senescence, canopy dieback, and mortality of plants in this habitat is demonstrated in both the summer months as well as prolonged periods of climatic drought (Coates et al. 2015). Coates et al. (2015) evaluated the combination of hyperspectral and thermal infrared imagery to monitor surface reflectance, compared change in land surface temperature (LST), and examined the potential for spectral mixture analysis to determine green vegetation from soil, shade, and non-photosynthetic vegetation (NPV). Multispectral sensors including the NIR, MIR, and the short-wave infrared (SWIR) have played important roles in distinguishing bare ground from healthy vegetation. SWIR can distinguish the biochemical signal of water absorption in leaves to allow biophysical property estimation while MIR reflectance may be more sensitive to changes in forest biophysical properties than reflectance of visible and NIR (Boyd and Danson 2005).

The timing of satellite fly-overs and available imagery necessary to perform analysis on vegetation composition on Southern California plant communities effectively has been previously mentioned and studied by Dennison and Roberts (2003a and 2003b). Spectral mixing is a challenge at any resolution imagery, when pixels become blurred where land use or habitat types overlap, but with high-resolution imagery this can be especially confounding. This spectral mixing may contribute to confusion and misinterpretation between classes in supervised classification, so needs to be addressed, acknowledged, and features further verified in the field. The most accurate classification of distinct CSS habitat values between species has been detected during months of peak growth, and the shortwave infrared band has been shown most useful for exposing these differences (Dennison and Roberts 2003a).

2.2.2. NDVI

A traditional approach to perform a quantitative evaluation of relative abundance of green vegetation is the Normalized Difference Vegetation Index (NDVI). This allows classification of green biomass, creation of a leaf area index (LAI), determination of percent cover, and distinction of stressed vegetation from healthy vegetation. NDVI compares reflectivity of the infrared wavelengths and absorption of red, visible wavelengths captured by multispectral imagery; a high NIR value (near 1) indicates healthy vegetation, while a low value falls between -1 and 0 and indicates stressed or dead vegetation (Warner and Campagna 2013). Chlorophyll reflects NIR waves in healthy, green vegetation, while it absorbs visible red; in stressed vegetation, plants do not make chlorophyll, and as a result, less infrared and more red and blue are absorbed. The formula (NIR – Red)/ (NIR + Red) is used to perform the calculation.

NDVI is commonly used to distinguish vegetation from anthropogenic area for land use change detection and comparing to outputs of supervised classification (Bhalli et al. 2013; Fernández, Paruelo, and Delibes 2010; Shirazi 2012). Green vegetation change in images can be performed by image subtraction (overlay) or a calculation of digital number (DN) values (Warner and Campagna 2013). The DN is an intensity value assigned to a pixel which can indicate its brightness or gray level, which is used for comparison of radiation or reflectance properties of surface substrate (Warner and Campagna 2013). NDVI can also be an indicator of primary production, the land surface brightness temperature, and the albedo reflectance of surface radiation.

2.2.2.1. False Color Composite

Creating a false color composite (FCC) from the NIR, red, and green bands, applying atmospheric correction, band stretching, band combination manipulation, and contrast adjustment are important techniques used in the process of imagery classification and NDVI. One of the most frequently published combinations uses near infrared light as red, red light as green, and green light as blue (EROS 2013; Aranoff 2005). In this case, plants reflect near infrared and green light, while absorbing red, which makes the healthy vegetation stand out with a deep red color. This band combination is valuable for gauging plant health and is an important technique for visual analysis to distinguish areas of living and dead vegetation. False color composite images are commonly used for distinguishing biophysical properties, which is possible because leaf chlorophyll compounds reflect NIR and expose healthy green vegetation as bright red (Aranoff 2005).

2.2.3. Panchromatic Bands

Panchromatic imagery has long been used for studying vegetation change in Mediterranean ecosystems (Carmel and Kadmon 1998; Kamiran and Sarker 2014). This supports high-resolution supervised and neighbor classifications to distinguish vegetation classes. One of the strengths is distinguishing classes by identifying various textures (Kamran and Sarker 2014). It is not uncommon that spectral mixing occurs with high-resolution bands (Dennison and Roberts 2003a and 2003b) and that field ground truthing must be performed to validate the results of classification.

2.3. Image fusion and Pansharpening

The panchromatic band often has a much higher spatial resolution than multispectral bands on the same satellite. For example, the eight WorldView-2 satellite multispectral bands are 1.84 m resolution while the panchromatic band is 0.46 m. Image fusion is the process of combining information from two images, and a common application is to sharpen 3-band multispectral imagery with higher resolution panchromatic to enhance digital classification accuracy (Aranoff 2005). There are multiple methods of pansharpening, including bilinear resampling, Gram-Schmidt method, and Brovey-transformation/color normalization of false color composite (EROS 2017). Pansharpening may be used to interpret vegetation structure, distinguish bare ground, and identify dead from living vegetation (Wang et al. 2011). In this thesis, pansharpening was used for comparing the dead and living vegetation and was a key asset in enhancing the false color composite image for supervised classification.

Pansharpening enhances the detail of the bands to maximum resolution of the input bands to provide highest digital classification accuracy, and an enhanced ability to visually interpret information (Aranoff 2005). It allows an image analyst to obtain information at a finer spatial grain.

Chapter 3 Methods

This chapter provides a description of the study area, the data and the data sources employed, the techniques implemented to extract habitat structure information, and the geostatistical methods used to explore possible connections between the PPM and its environment. To explore the relationship between the spatial distribution of the PPM presence and its habitat, three general techniques were used: image extraction within GIS software (Idrisi, Clark Labs, Worcester, MA) was used to perform supervised classification for development of environmental variables, GIS (ArcMap 10.5.1 and ArcGIS Pro 2), Esri, Redlands, California) was used to analyze and reclassify data, and Maxent (Philips, Dudik, and Schapire, Center for Biodiversity Conservation at the American Natural History Museum, New York, New York) generated the species distribution models. The imagery was also analyzed using NDVI to measure change in vegetation health and incorporated into the SDM as well as evaluated as an independent index. Additionally, a digital elevation model (DEM) was processed and included in the model.

3.1. Data Description

3.1.1. PPM presence data

PPM location (presence) data were essential to modeling the distribution and occupancy of suitable habitat (CNLM 2010). These data were developed using the positions of the survey grid cell placed over an aerial image of the site in GIS, and field researchers' placement of the trap within 5–8 m of that point in open soil. A Trimble GeoXT Global Positioning System (GPS) receiver with submeter accuracy was used to locate the grid cell point in the field for conducting the survey and acquiring the location of the detected species (CNLM 2010). The trapped species locations were in two separate GIS shapefiles, one for south of Old Marguerita Road and the other for north of the road. These were combined and entered into a simple CSV file with columns only for the species name, UTM Northing and UTM Easting coordinates for use in the Maxent software. PPM presence data was acquired from the CNLM's online Box document storage system with permission from Science Director Dr. Deborah Rogers.

3.1.2. Digital Globe Imagery satellite imagery-derived environmental variables

Due to limitations of available environmental variable datasets from the Preserve, imagery played an important role in creating the layers necessary for the species distribution model. Various kinds of publicly available imagery, including Landsat and Earth Resources Observation Satellite (EROS), were evaluated for their spatial, spectral, temporal, and radiometric resolution to fit the project needs (Table 4). The WorldView-2 satellite was launched in October 2009, and is the first high-resolution 8-band multispectral commercial satellite. It operates at an altitude of 770 kilometers, and provides 46 cm panchromatic resolution in addition to the 1.84 m multispectral resolution. The recapture interval of 1.1 days makes it a good option for conducting repeat imagery and having a wide source of available imagery.

Table 4. Comparison of resolution between common available satellite imagery

Satellite	***Time Span***	***Number Bands***	***Panchromatic Band***	***Spatial Res. (m)***	***Available***	***Producer***
Landsat 7	1999-present	8	Yes	15–60	Public	USGS/ NASA
EROS ASTER	1971 - present	14	Yes	15	Public	USGS/ NASA
WorldView -2	2010 - present	9	Yes	0.46–1.84	Commercial	Digital Globe

WorldView-2 imagery met criteria of cloud cover and seasonality for May 29, 2010, May 25, 2014, and April 24, 2017. Additionally, the images had been atmospherically and radiometrically corrected as well as georeferenced, so minimal pre-processing was required.

Unfortunately, the satellite had not been launched in early 2009, so imagery was not available for the year when the highest number of PPM was captured and 2010 imagery was used instead. The 2014 imagery was used as a comparison, but because of the absence of trap data from that year it could not be used in a model. The difference between environmental conditions in 2014 were too great to correlate the 2012 trapping data to the latter imagery. Additionally, there were insufficient PPM locations available from 2017 to develop a separate model for that year. Imagery was obtained from April and May during the peak of coastal sage scrub vigor, as well as to coincide with approximate timing of the PPM surveys. Digital Globe Imagery provided the imagery as grant through their educational Digital Globe Foundation.

Standard images have three bands, a red, green, and a blue that capture wavelengths on the electromagnetic spectrum which are visible to the naked eye. Multispectral bands detect information using wavelengths that are not visible, that can expose more detailed information about phenomena that are being remotely sensed. The eight multispectral bands of WorldView-2 contain two near infrared bands, a red, and a red-edge (Figure 12), all of which contribute to vegetation health/vigor analysis using NDVI measurements. Each of those bands has a unique spectral capture for vigor of chlorophyll, leaf absorption, or reflection.

THE ROLE OF EACH SPECTRAL BAND

Coastal Blue (400-450 nm) ▪ New band ▪ Absorbed by chlorophyll in healthy plants and aids in conducting vegetative analysis ▪ Least absorbed by water, and will be very useful in bathymetric studies ▪ Substantially influenced by atmospheric scattering and has the potential to improve atmospheric correction techniques	**Red (630-690 nm)** ▪ Narrower than the red band on QuickBird and shifted to longer wavelengths ▪ Better focused on the absorption of red light by chlorophyll in healthy plant materials ▪ One of the most important bands for vegetation discrimination ▪ Very useful in classifying bare soils, roads, and geological features
Blue (450-510 nm) ▪ Identical to QuickBird ▪ Readily absorbed by chlorophyll in plants ▪ Provides good penetration of water ▪ Less affected by atmospheric scattering and absorption compared to the Coastal Blue band	**Red-Edge (705-745 nm)** ▪ New band ▪ Centered strategically at the onset of the high reflectivity portion of vegetation response ▪ Very valuable in measuring plant health and aiding in the classification of vegetation
Green (510-580 nm) ▪ Narrower than the green band on QuickBird ▪ Able to focus more precisely on the peak reflectance of healthy vegetation ▪ Ideal for calculating plant vigor ▪ Very helpful in discriminating between types of plant material when used in conjunction with the Yellow band	**NIR1 (770-895 nm)** ▪ Narrower than the NIR1 band on QuickBird to provide more separation between it and the Red-Edge sensor ▪ Very effective for the estimation of moisture content and plant biomass ▪ Effectively separates water bodies from vegetation, identifies types of vegetation and also discriminates between soil types
Yellow (585-625 nm) ▪ New band ▪ Very important for feature classification ▪ Detects the "yellowness" of particular vegetation, both on land and in the water	**NIR2 (860-1040 nm)** ▪ New band ▪ Overlaps the NIR1 band but is less affected by atmospheric influence ▪ Enables broader vegetation analysis and biomass studies

Figure 12. Description of the Multispectral bands of the Digital Globe WorldView-2 Satellite
Source: Digital Globe 2009

A multi-stage process was undertaken to prepare each set of imagery as environmental input variables for Maxent (Figure 13). The imagery was acquired from Digital Globe in two separate .TIL files, with one image of multispectral 1.84 -m bands and the other 0.46 m resolution panchromatic band. These were both clipped down to an extent capturing the Preserve and surrounding area and stored as a .TIF format using ArcMap. Each file was then imported into Idrisi using the GDAL converter to create .rst files for image processing. Each band of the imagery was manually set to optimal contrast using greyscale palette, then combined with the panchromatic band in the process known as pansharpening to improve the resolution of the multispectral bands to 0.49 m spatial resolution.

A false color composite of the imagery was created using the NIR band 7 as red, the red band 5 as green, and the green band 3 as blue. Training areas were developed and eleven training group categories were created; Ocean, Beach, Bluff Rock, Bare ground, Asphalt, Houses, Landscape, *Encelia californica* (Sunflower), *Eriogonum fasciculatum* (Buckwheat), *Rhus integrifolia* (Lemonadeberry), and *Artemisia californica* (Sagebrush). Separate training groups were created for each of the 2010 and 2017 images because of changes in Nadir of the satellite and various compositions which were visible in each year.

Once the vector training groups were developed, they were converted to signature files and put into a signature group for inclusion into supervised classifiers. The spectral signature comparison was run to analyze spectral overlap between classes, and new training polygons were added and new spectral signatures were created as necessary to improve the outputs. Four different sets of training polygons and signatures were developed, with each process increasing the number of pixels correctly categorized in vegetation and bare ground classes found within the Preserve area. It was challenging to train the detection of important features within the Preserve because of the amount of landscaped area outside the boundary which was creating spectral confusion within Idrisi. As discussed in the literature review, spectral mixing can be a challenge in distinguishing subtle detail as pixels become blurred in areas such as overlapping vegetation and bare ground at high resolution. Visual inspection of the classification and categories was used to determine the final appropriate pixel classifications which were used for the model

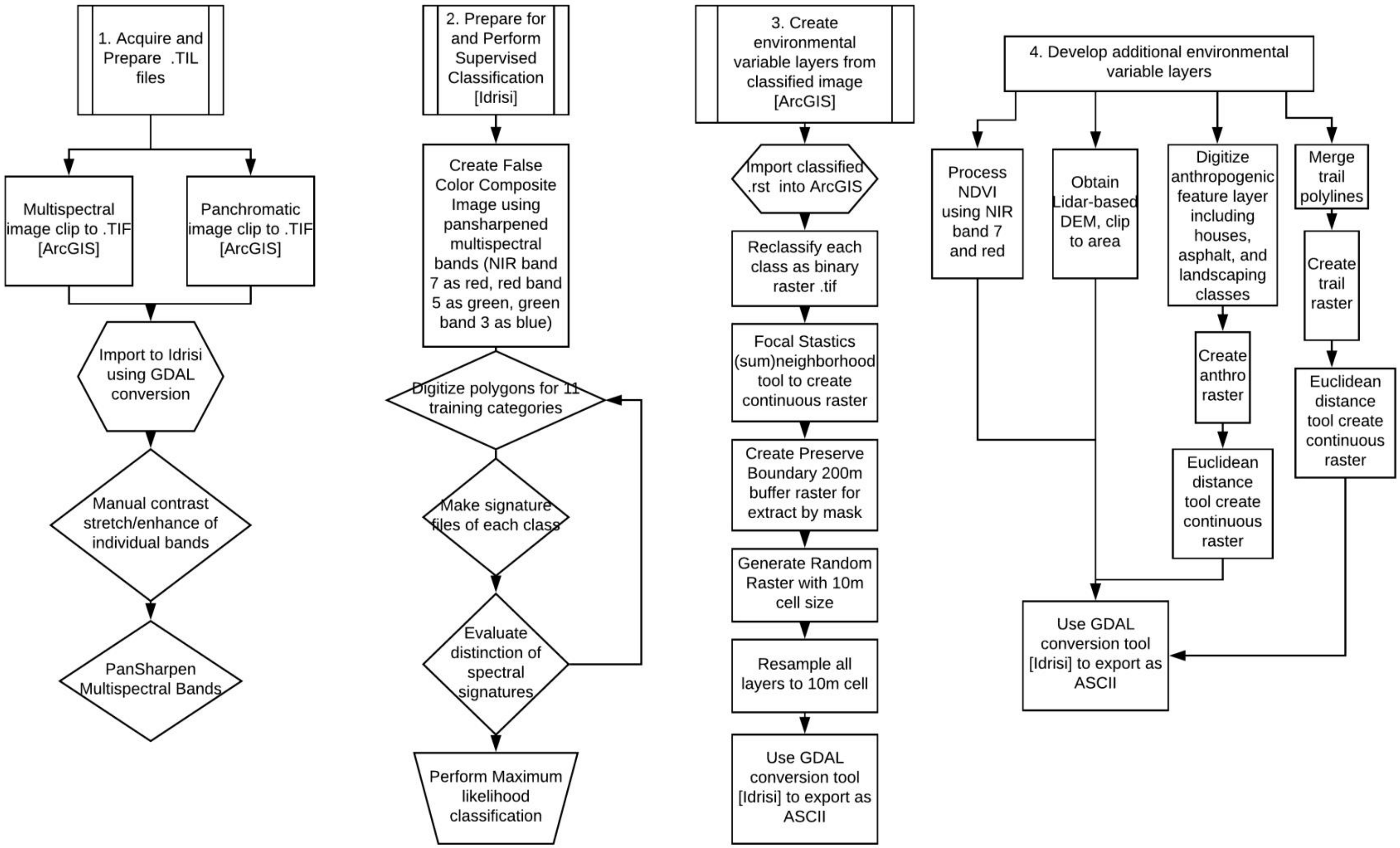

Figure 13. Image Processing Workflow

Multiple hard classifiers were run and visually examined for their best accuracy given field knowledge of the site. The MaxLike classifier relies on having *a priori* knowledge of the site, and produced the best results based on probabilities of each class which were assigned to each class and run through the program for both 2010 and 2017 (Table 5). The images were taken at a similar time of year within a month window, seven years apart.

Table 5. Probability of likelihood assigned to each training category for MaxLike classifier for 2010 and 2017 imagery

Group	***Class***	***Assigned Likelihood***	
		2010	***2017***
1	Ocean	0.1	0.05
2	Beach	0.05	0.05
3	Bluff Rock	0.1	0.1
4	Bare Ground	0.15	0.15
5	Asphalt	0.1	0.1
6	Houses	0.1	0.1
7	Landscape	0.1	0.1
8	Sunflower	0.05	0.05
9	Buckwheat	0.1	0.1

Once the image classifications were performed, the rasters were converted to ASCII format using the Idrisi GDAL converter to perform the first runs of the Maxent model, using a *categorical* value for the classified imagery and spatial resolution of 0.49 m. The pan-sharpened multispectral bands were converted to ASCII and contributed as *continuous* environmental variables to the model. These results yielded reason to run the model at a higher spatial resolution to accommodate pixel placement to the approximate area of the PPM traps.

Next, the training groups were re-assigned signatures using the non-pansharpened imagery to run the model with layers resampled from 1.86 m to 2 m. Similarly, a categorical environmental variable with all eleven classes was run in the model with each of the multispectral bands. The results still yielded uncertainty about model performance so new rasters were created at 10 m resolution.

To prepare 10 m environmental rasters, the pan-sharpened categorical rasters were converted to binary rasters representing each vegetation type of interest as well as bare ground using the Reclass tool in Idrisi. These were added together using the Image Calculator to confirm that there were no overlapping pixels, and that each pixel was assigned to only one class. The images were imported to ArcMap for resampling and clipping.

Once integrated into ArcMap, the images were saved as .TIF files from .rst files. The Focal Statistics tool was used to calculate sum of each vegetation type within a 3 m by 3 m neighborhood area. A Random Raster was created with 10 m cell size using the processing extent of the larger Dana Point area image, and the image was resampled to a larger cell size using that 10-m grid. Images were clipped to a 200 m Preserve buffer raster and exported as ASCII files using the GDAL conversion tool in Idrisi.

To understand the influence that distance to houses and asphalt may have in contributing to the spatial distribution of PPM, a separate anthropogenic layer was created based on those classification outputs. The three classes (houses, asphalt, and landscaping) were combined using the Reclassify tool, and digitized into a vector shapefile. This layer of anthropogenic features was rasterized (in ArcGIS) and Euclidean distance was run at a 10 m interval on the 0.5 m anthropogenic variable. Distance rasters were created at the 0.5 m and resampled to 10 m resolution then exported to ASCII files for use in Maxent.

The recreational trail that traverses the perimeter of the Preserve was also processed as a distance raster to incorporate into the model. The original trail shapefile had been digitized as multiple polylines from an aerial photo for use in cartographic maps, so these were first merged into one line, re-projected from State Plane Zone V (FIPS) to UTM Zone 11N coordinates, then rasterized as a binary layer. A Euclidean distance tool was run on 0.5 m resolution cell size, then resampled to 10 m.

An NDVI layer was also developed from the imagery as an environmental input variable. NDVI was performed in Idrisi using the NIR band seven (7) and red pansharpened band five (5), reclassified to values between -1 to 1, then resampled to the 10 m resolution to match the other layers. As with all the environmental variable layers, it was clipped to the 200 m Preserve boundary buffer raster before exporting to ASCII format.

3.1.3. Lidar-based environmental variables

Because there is little known about microtopography preference of the PPM except that it prefers to live under 600 m elevation (Federal Register 2004), this was considered in the SDM as well. High- resolution digital elevation model (DEM) captured at the same spatial scale as the highest resolution of the imagery (0.5 m) was obtained. The 2016 USGS West Coast El-Nino LiDAR DEM project (NOAA 2016) produced high accuracy 3D elevation products and 0.5 m cell size DEMs that suited this model. The dataset was clipped to the preserve extent, used to create slope and aspect to understand the influence that these might have on the PPM, then downsampled for compatibility with the model. The slope and aspect were prone to overfitting to the data in the preliminary Maxent models and were not used for the final models.

3.2. Research Design

The overall method was to use the Maxent program to model the 2009 species trapped locations with environmental variables in raster format that were derived from high-resolution, multispectral satellite imagery. Image processing was also performed on 2017 imagery to detect changes between the two years which may explain change in species distribution. The imagery for the project was high-resolution WorldView-2 imagery (8-band multispectral at 1.84 m resolution at GSD and 0.46 m panchromatic band) provided by a grant from Digital Globe. The highest resolution imagery possible was necessary to complete the classification and perform vegetation comparisons. However, after running the first Maxent models it was determined that downsampling was necessary to create an appropriate spatial resolution that incorporated the variability within pixels surrounding the documented location of the PPM location at the scale that would influence the mice. The composition of vegetation and bare ground around the trap location was more important than the exact pixel, so the focal statistics tool was used to estimate vegetation cover in specified areas and resampled to create the 10 m areas of analysis.

All raster layers were clipped, extracted by mask, given the correct environments, and saved as TIF files to be prepared for conversion to ASCII (using the GDAL conversion tool in Idrisi) with the same bounding coordinates and cell size. The final input variable layers used are Distance to Trail, Distance to Houses, DEM, NDVI, bare ground, sagebrush, lemonadeberry, buckwheat, and sunflower. The Maxent program was chosen because of its ability to filter the conditions at the pixel where the species are present to other areas in the image, and for the extensive outputs that it develops.

Chapter 4 Results

The results of the Maxent models were highly variable depending on environment settings. Permutation importance and individual environmental variable contribution to the model changed substantially depending on the number and type of variables included. Maxent was an adaptively managed tool to which variables were added and removed based on their contributions and ability to contribute to an ecologically reasonable model.

4.1. Image processing results

To develop environmental variable layers, each step of image processing relied on continuous analysis and refinement of layers. As mentioned in the earlier chapters, a false color composite image was created using the greyscale contrast-enhanced, pansharpened NIR band 7, red band 5, and green band 3 to highlight living vegetation contrasts. Eleven vector training groups were digitized using polygons on each 2010 and 2017 imagery to identify the four major dominant vegetation types and other features of interest (Figure 14).

Comparing the spectral signatures of the training groups was one measure of the way each class would be distinctly classified. With excessive overlap in spectral signature, there would not be appropriate distinction between the vegetation/habitat types, and the training group polygons would necessarily be redigitized. This process was repeated to obtain distinct classifications, though there was some overlap between the landscape category with the others in the final output. Unfortunately, some class overlap could not be avoided, which may have contributed to the model performance and some surprises between the anticipated and actual outputs.

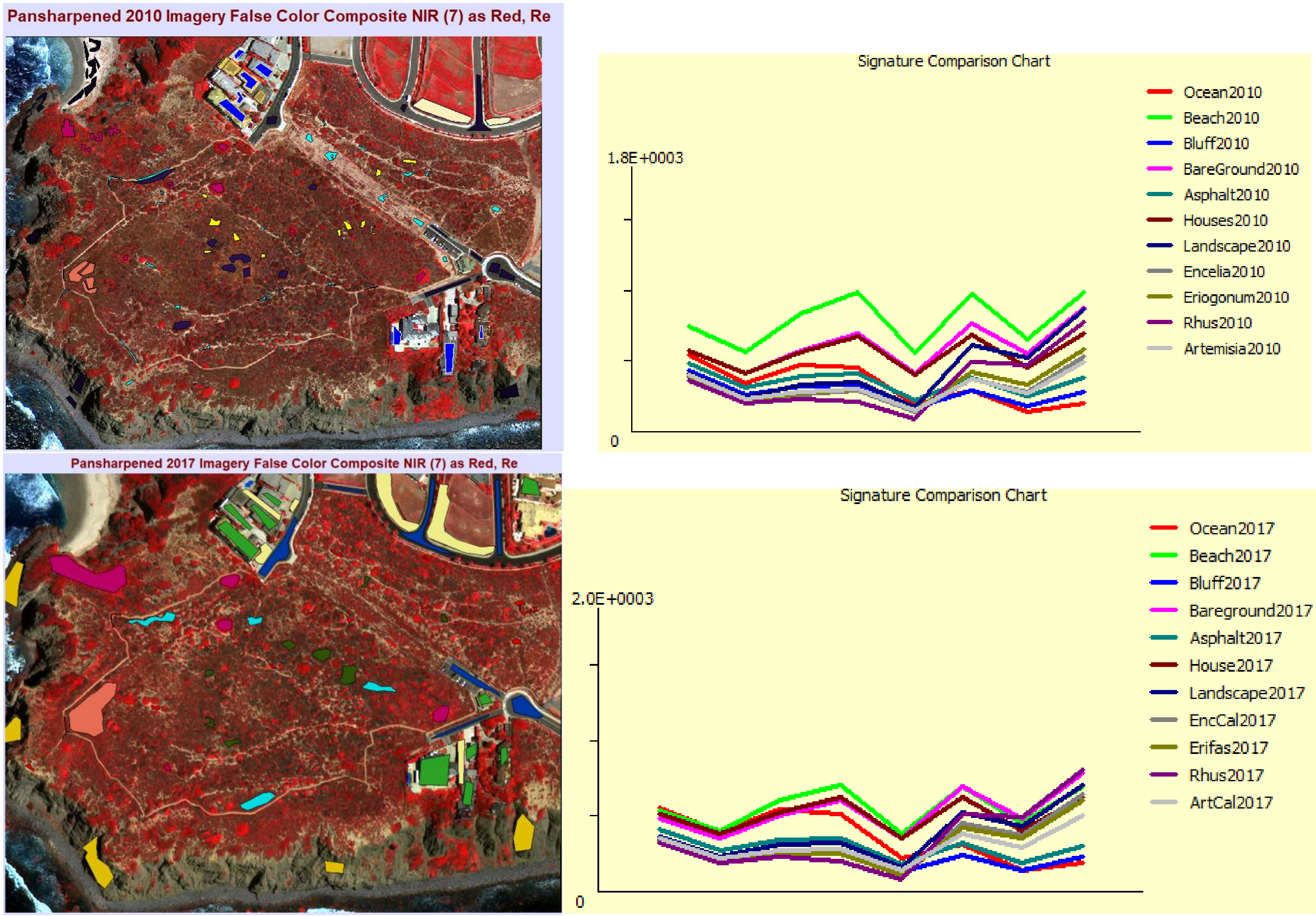

Figure 14. Polygons created for 2010 and 2017 training groups and their spectral signature comparisons

4.1.1. MaxLike Classifications

Field knowledge of the site allowed selection of probability for each class, which was entered into the MaxLike (Maximum Likelihood Classifier) as shown in the Methods section. Results for the 2010 imagery indicated highest vegetation covers on the site with 19% covered by sagebrush, 21% buckwheat, small amounts of lemonadeberry (5%) and sunflower (3%), with 9% bare ground (Table 6).

Table 6. Classification results for 2010 imagery

Class	***Name***	***Frequency***	***Percent***
1	Ocean	64644	7
2	Beach	5504	1
3	Bluff Rock	77422	10
4	Bare Ground	55313	9
5	Asphalt	32962	4
6	Houses	87592	10
7	Landscape	130145	11
8	Sunflower	25197	3
9	Buckwheat	108170	21
10	Lemonadeberry	36317	5
11	Sagebrush	177259	19

Classification of the 2017 imagery revealed twenty percent (20%) total cover of sagebrush, a decrease in Buckwheat to 14% cover, six percent cover of lemonadeberry, five percent (5%)of sunflower, and a total cover of twelve percent (12%) bare ground (Table 7). Biologically, these changes can be explained, and additionally can be validated in the field. There have been changes in vigor as well as growth in the vegetation between the two years, most noticeably where the new age vegetation has grown in the restoration area, and large stands of buckwheat have died. Lemonadeberry has grown larger and maintained dense leaf area, sunflower responds to high rainfall with incredible vigor, buckwheat has aged and has less leaf surface area as the branches become woody, and bare ground has become more evident underneath dead vegetation. Sagebrush has remained in similar size stands, with growth patterns highly responsive to rainfall.

Table 7. Class percentages and frequency for 2017 classification

Class	***Name***	***Frequency***	***Percent (%)***
1	Ocean	34483	4
2	Beach	16737	2
3	Bluff/Rock	94831	11
4	Bare ground	93685	12
5	Asphalt	54315	7
6	Houses	66518	8
7	Landscape/Ornamental	78032	11
8	Sunflower	42463	5
9	Buckwheat	105714	14
10	Lemonadeberry	50162	6
11	Sagebrush	163585	20

In summary, there were evident changes among vegetation classes that can be explained by the change in habitat or impacts from the surrounding area. The imagery used for the classification extended to a 200-m buffer beyond the Preserve boundary to include analysis of the external influences on the PPM, which contributed to the total percentages of each category (Table 8). The imagery was clipped to the Preserve boundary so that new total percentages could be compared for change (Table 9).

Table 8. Differences between classifications in 2010 and 2017 imagery using classified imagery with 200 m Preserve Boundary buffer

Class Name	***Percent 2010***	***Percent 2017***	***Change***
Bare ground	9	12	+3
Sunflower	3	5	+2
Buckwheat	21	14	-7
Rhus	5	6	+1
Artemisia	19	20	+1

Table 9. Percent change in counts using classified imagery clipped to Preserve boundary

Category	***2010 Percent (%)***	***2017 Percent (%)***	***Change***
Bare ground	11	14.4	3.4
Sunflower	5.25	8.2	3
Buckwheat	28.5	18.2	-10.3
Lemonadeberry	5.5	7.6	2.1
Sagebrush	29.25	29	-0.25

4.2. Maxent Models

In total, four (4) models were run using the half-meter data, four (4) models were run using two-meter data, and twenty-eight (28) models were run using the ten-meter data. Of these models, three were run without replicate, three were run with five replicates, and thirty models were run with forty-five replicates. The preliminary 12 models were run without the full sample subset (missing two points that were stored in a separate GIS file and later discovered), so those were used solely to compare the performance of other models. The inclusion or omission of each environmental variable was adaptively chosen based on percent contributions in each model, the jackknife indication of training gain without the variable, and general fit to the model. For example, models that included the DEM variable seemed to “overfit” by showing an exaggerated influence; this was likely due to the steep bluff area leading to the ocean where PPM do not live, so this variable was excluded in progressive models. NDVI consistently lacked contribution to any of the models and was excluded from the later models as well; it displayed a regular, bell-shaped curve when run independently and was analyzed separately for its vegetation indices. Out of all the models, the most consistent contributions were cover of, proximity to anthropogenic features, proximity to the recreational trail, amount of sagebrush and cover of buckwheat.

4.2.1. Preliminary Maxent models

Models using 0.5 m and 2 m resolution were run using categorical vegetation layers. However, this large spatial scale did not represent the influence that habitat composition around the trap area has on the PPM presence because Maxent makes its correlations based on pixel placement. This issue was resolved by using the Focal Statistics tool and downsampling the imagery to 10 m cell sizes to match the scale of movement of PPM.

4.2.2. Imagery reclassification

The categorical classification was separated into individual binary rasters in Idrisi, using the Reclassify tool to assign values of 0 to all categories other than the category of interest, which was assigned a value of 1 (lemonadeberry example in Figure 15). Each vegetation category was created as the foundation of an environmental variable layers at 0.5 m resolution., then imported into ArcGIS and clipped to the buffered Preserve area. Each raster was processed using the Focal Statistics tool to add the pixels (Sum) within a nearest neighbor area of 3 x 3 (Figure 16), then resampled to 10 m resolution using a Random Grid 10 m Raster. (Figure 17).

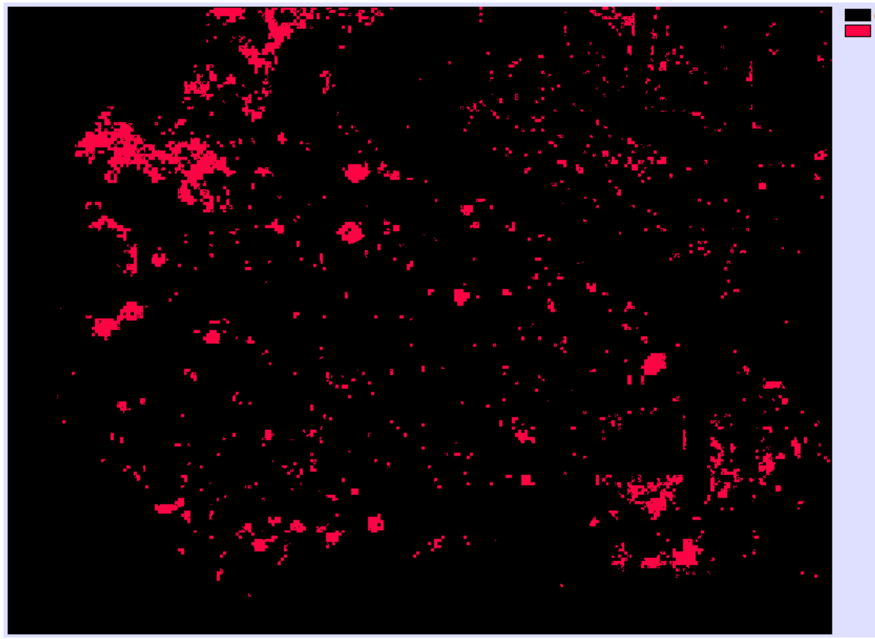

Figure 15. Example of lemonadeberry vegetation layer binary classification

Figure 16. 0.5 m Lemonadeberry example of spatial resolution after Focal Statistics

Figure 17. 10 m Lemonadeberry example of resampled raster

The downsampled raster allowed a gradient of the pixels to be considered in the Maxent analysis at a resolution that is biologically relevant to the activity pattern of PPM. The anthropogenic feature polygon was rasterized (in ArcGIS) and the Euclidean distance tool was used to create a distance raster for use in Maxent at both the 0.5 m and 10 m resolution (Figure 18). The darker black the color of the pixel, the closer it is to the feature. Conversely, areas in white are the furthest from the houses.

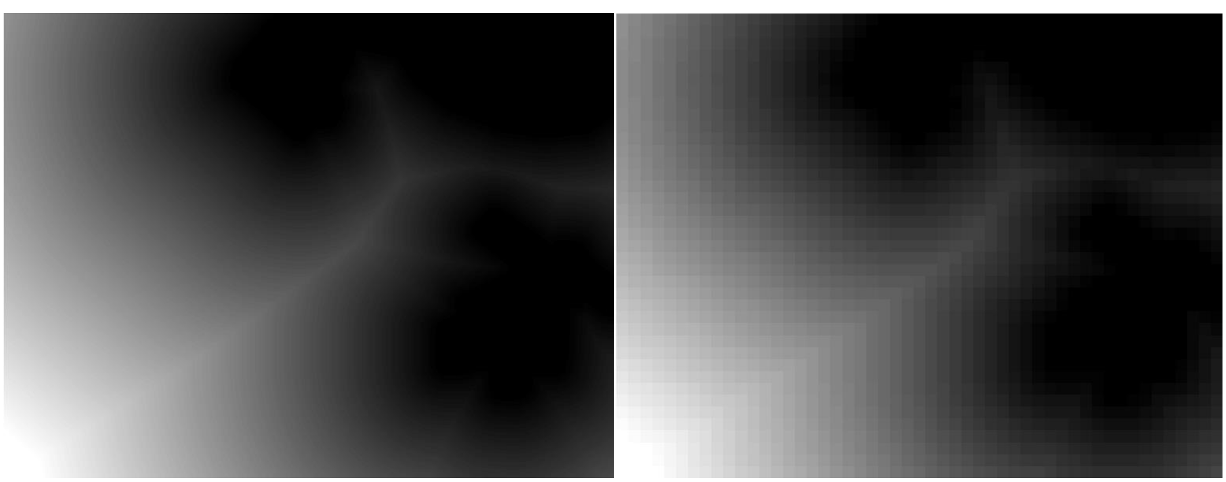

Figure 18. Distance to anthropogenic features at 0.5 m and 10 m resolutions

Similarly, the Euclidean distance tool was run on the 0.5 m trail layer to create a continuous raster, then downsampled to 10 m for the models (Figure 19). Finally, the 0.5 m DEM was downsampled (using the 10 m Random Raster) and prepared for the coarser Maxent model (Figure 20). Each layer was clipped to the buffered preserve area.

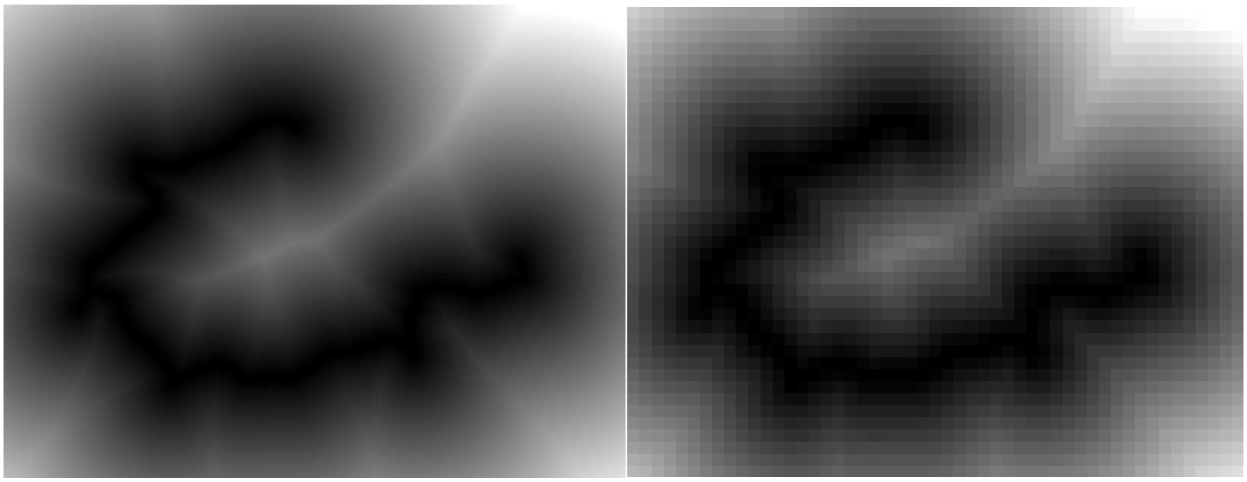

Figure 19. Distance to trail raster at 0.5 m and 10 m spatial resolution

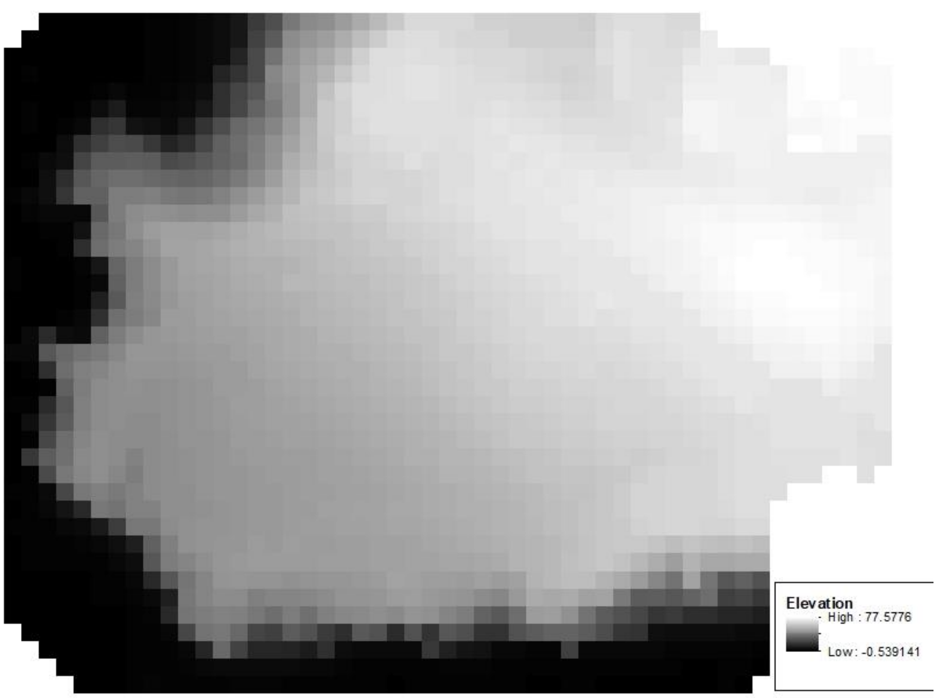

Figure 20. 10 m spatial resolution DEM

The process of creating appropriate environmental variables was an important and time-consuming process of accurately capturing critical information to the pixel-dependent Maxent program.

4.3. Final Maxent models at 10 m spatial resolution

Given the full set of PPM presence points and using all the 10 m continuous environmental variables, patterns began to emerge as they were chosen for inclusion or exclusion with successive replicates. Each set of models was started with all nine environmental input variables (distance to anthropogenic features, distance to trail, sagebrush, lemonadeberry, sunflower, buckwheat, bare ground, NDVI, and DEM), then variables were progressively omitted after evaluation of their contributions. As mentioned previously, NDVI and DEM were eliminated from models early in the test process as they continuously overfit with contribution and permutation importance. Models were run with 45 replicates using a multiplier of 1, then tested for performance at 2 in order to develop the smoothest models with the most realistic results.

Cloglog and logistic feature types were tested for best performance, and output formats of auto, linear, quadratic, and hinge were similarly experimented. The logistic model creates an exponential function of the environmental variables, while cloglog gives an estimate between 0 - 1 for presence. Maxent creates a piece-wise linear model when using hinge features, so it creates a connected line response curve. The linear model is supposed to generate continuous variables close to their observed mean values at occurrence localities while quadratic demonstrates variance of continuous variables that should be close to observed values. Philips et al. (2006) suggest the linear and quadratic for sample sizes under 80, however for this data, the most consistent outputs were determined using the hinge output format and the cloglog feature type with a multiplier of one. Examples of these outputs (Table 10) show the consistently high permutation importance of distance to anthropogenic features, distance to trail, and sagebrush presence as influences on the distribution of the PPM.

Using the five variables which consistently contributed to the models without overfitting (sagebrush, distance to anthropogenic features, buckwheat, distance to trail, and sunflower) produced the result with the highest AUC and lowest standard deviation combination when run with the default multiplier of one. The environmental variable with the highest gain when used in isolation is distance to anthropogenic features, which appears to have the most useful information independently with a 45% permutation importance. The variable which decreased the gain the most when omitted is also the distance to anthropogenic features. The distance to anthropogenic features layer appears to have the most information that is not present in the other variables. All the input values shown are averages over the 45 replicate runs (Table 11).

Table 10. Sample of results using various input variables and Maxent settings

Input Environmental Variables (by permutation importance)	***# Reps***	***AUC***	***Std. Dev***	***Output format***	***Feature Type***	***Multiplier***
Distance to Anthropogenic Features + Distance to Trail + Sagebrush + Buckwheat + Sunflower	45	.813	.109	Hinge	Cloglog	1
Distance to Anthropogenic Features + Distance to Trail + Sagebrush + Buckwheat + Sunflower + NDVI + Bare Ground + Lemonadeberry	45	.805	.111	Hinge	Cloglog	2
Distance to Anthropogenic Features + Distance to Trail + Sagebrush + Buckwheat + Sunflower + Bare Ground	45	.810	.109	Hinge	Cloglog	2
Distance to Anthropogenic Features + Distance to Trail + Sagebrush + Buckwheat + Sunflower + NDVI + Bare Ground + Lemonadeberry	45	.805	.111	Hinge	Cloglog	1
DEM + Distance to Anthropogenic Features + Sagebrush + Distance to Trail + Buckwheat + NDVI + Sunflower + Bare Ground + Lemonadeberry	45	.827	.083	Hinge	Cloglog	1

Table 11. Highest performing model variables' percent contribution and permutation importance

Variable	**Percent contribution**	**Permutation importance**
Distance to Anthropogenic Features	34.2	45.0
Distance to Trail	24.5	27.3
Sagebrush	27.9	10.7
Buckwheat	8.1	11.6
Sunflower	5.3	5.5

The environmental variables were also assessed for their contribution to the model by using the jackknife function. Each step in the Maxent model increases the gain by modifying the coefficient for a single feature and the program assigns the feature to the environmental variable that the feature depends on. They are heuristically defined and depend on the path that the Maxent code uses to get to the optimal path solution, which means that there could be many paths and many percent contributions (which is why the outputs are averaged and multiple replicates are used to "smooth" it out). If the jackknife achieves no gain, then the interpreter will know that it is not very useful for independently estimating distribution of PPM; this shows the relative importance in the test gain versus the training gain and whether the model is obtaining a good fit for Maxent to the training data (Philips and Dudik 2008).

Looking at the response curves also demonstrates how each environmental variable affects the Maxent prediction. The curves show the way predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. The curves can be deceiving with strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. For this reason, the variables were included only if their contribution was realistic. In the representation outputs, the curves may show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together. The curves show the mean response of the 45 replicate Maxent runs (red) and the mean +/- one standard deviation (blue). The Maxent model creates alternative response curves using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. The environmental variable responses were relatively consistent when tested as part of the model and independently, showing regular distribution (Figure 21). The maximum distance from the anthropogenic features to the edge of the Preserve before it drops off into the ocean is about 250 m. It is important to note that the distance to anthropogenic features and the distance to trail variables experience steep declines at that point where they hit the Preserve boundary.

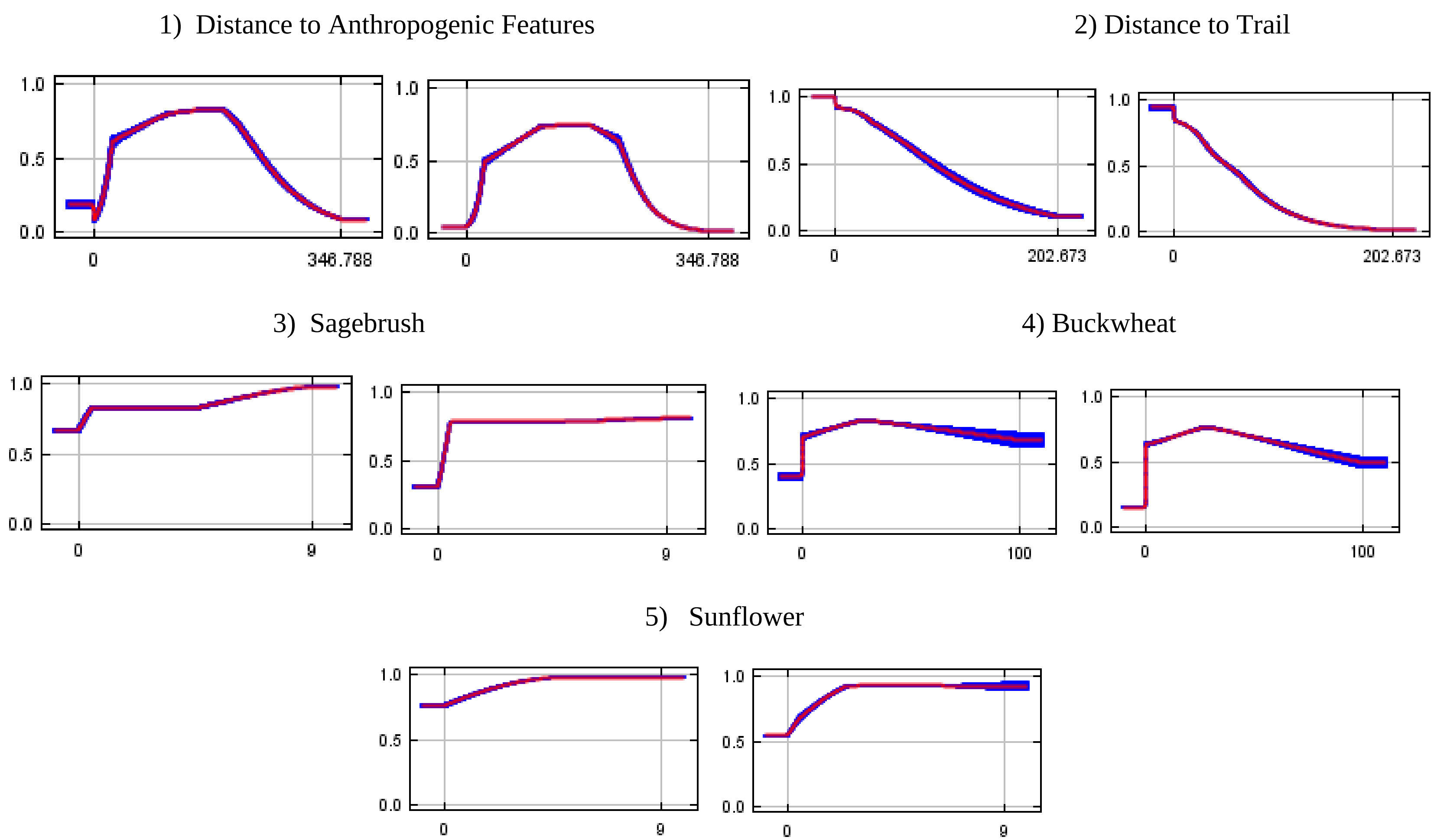

Figure 21. Contributions of environmental variables compared by importance in the model (left) and independently (right) with PPM presence

The receiver operating characteristic (ROC) curve is another way to show commission for the same data, again averaged over the replicate runs. The average test AUC for the replicate runs is 0.813, and the standard deviation is 0.109 (Figure 22). This indicates that the model performed better than random prediction.

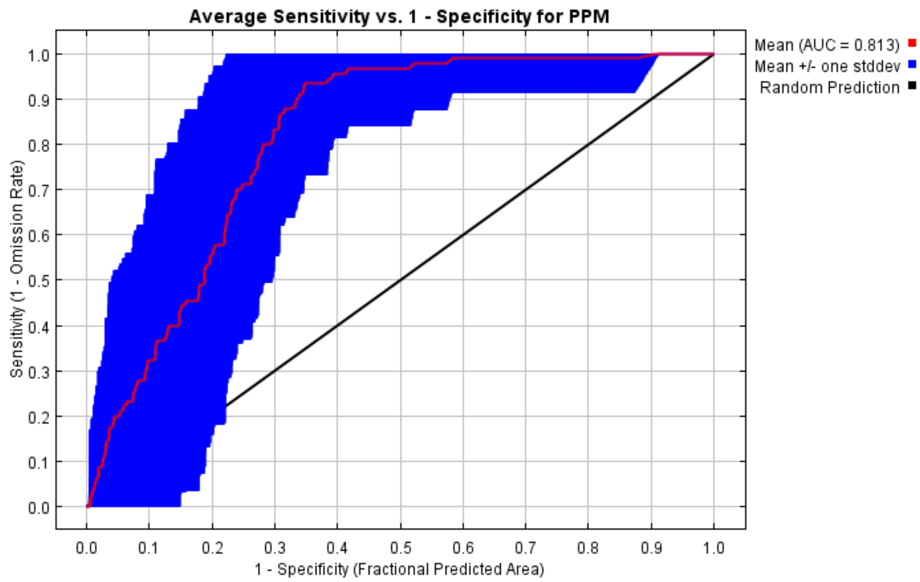

Figure 22. Receiver Operating Characteristic of top performing Maxent model

An additional output of Maxent was performing the test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs. The actual omission rate followed the predicted omission within an acceptable amount of deviation (Figure 23). These measures of model performance are used to complement the graphical output of anticipated species distribution based on the known presence locations. The pointwise mean graphic output exhibited confidence intervals that ranged from 0–1. It accurately showed that ocean and bluff were not places likely to find PPM (in blue). Conversely, there is a lot of red “color” in the southern part of the Preserve which identifies area that are suitable and unoccupied (Figure 24). The area northeast of the old road also shows limited suitability.

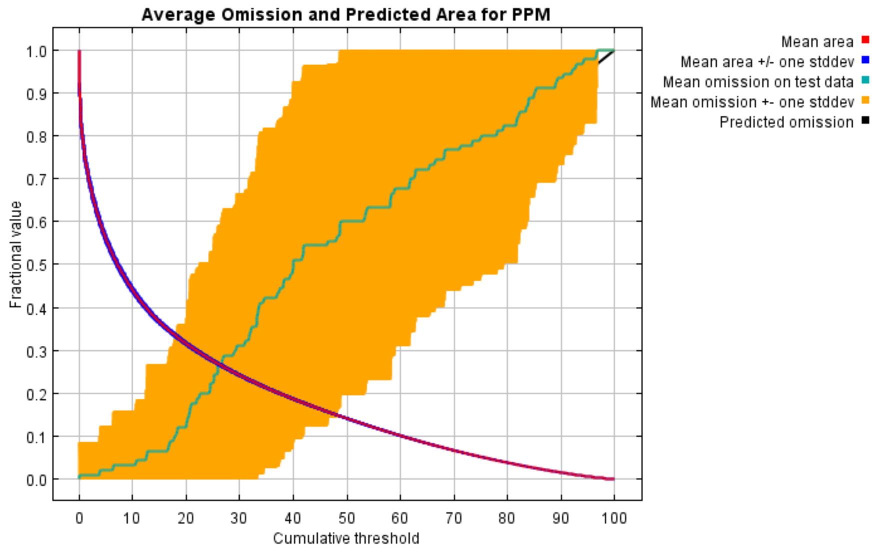

Figure 23. Omission rates for top performing Maxent model

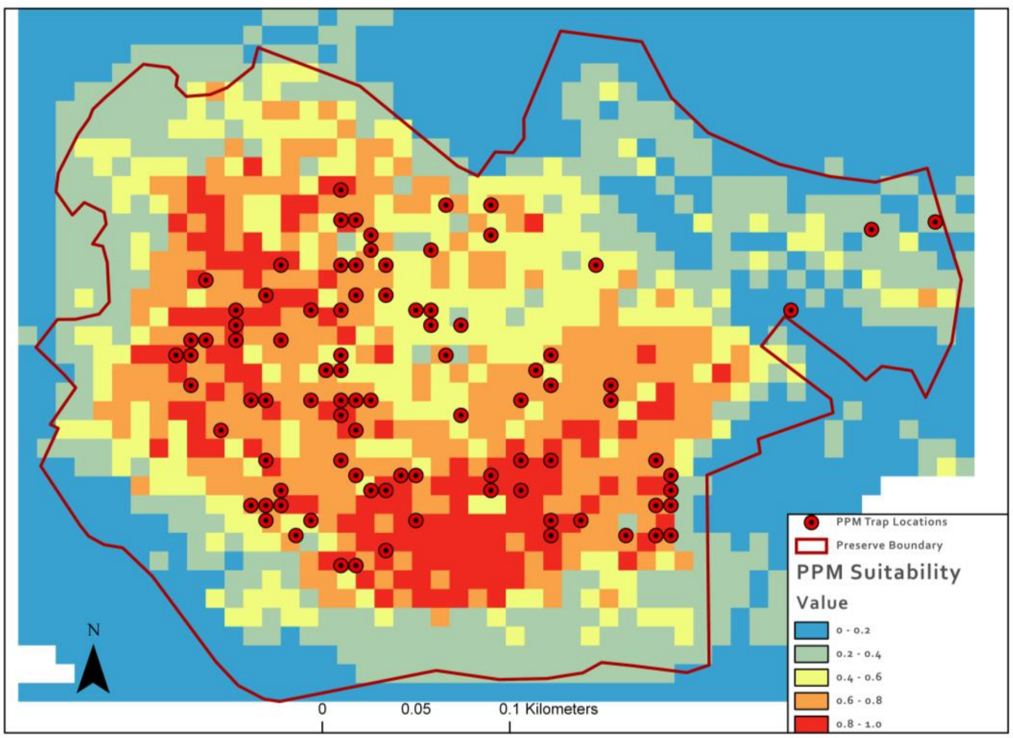

Figure 24. Point-wise mean (average) of points in the model with 2009 presence locations

The sample size of six unique individuals trapped in 2017 was too small for the Maxent program to provide meaningful information about relationship between PPM presence and distribution in the habitat, however, other trends can be evaluated by comparison with the 2010 values. Change in vegetation cover has been observed in the field from 2010 to 2017, as stands of sagebrush and buckwheat mature and face changing temperature and rainfall patterns. The vegetation classifications reveal interesting differences, and a comparison of NDVI can also illuminate potential factors in change in habitat which may have shifted the PPM species distribution.

4.4. NDVI

Analysis of NDVI was conducted independently from the Maxent model to compare change in plant vigor and bare ground between 2010 and 2017. The absorption of wavelengths in the red visible range and reflectance of healthy leaves in the NIR create the contrast in spectral properties between wavelengths which provide information about dead versus living vegetation. Values of less than zero (0) contain water, bare ground falls between values of 0–0.1, shrubs are between 0.2 and 0.5, while dense forest cover is between 0.5–1.0 (USGS 2015). NDVI analysis of the 2010 imagery using the pansharpened red band 5 and NIR band 7 shows the contrast between the bare ground reflectance and the living vegetation (Figure 25). The image was clipped to the Preserve boundaries to evaluate the histogram and change in the PPM habitat. Evaluating the histogram at intervals appropriate to USGS class covers, bare ground covered 8% and 64% of the ranges fell between 0.2–0.5, appropriately indicating shrub cover (Table 12). The mean value was 0.31.

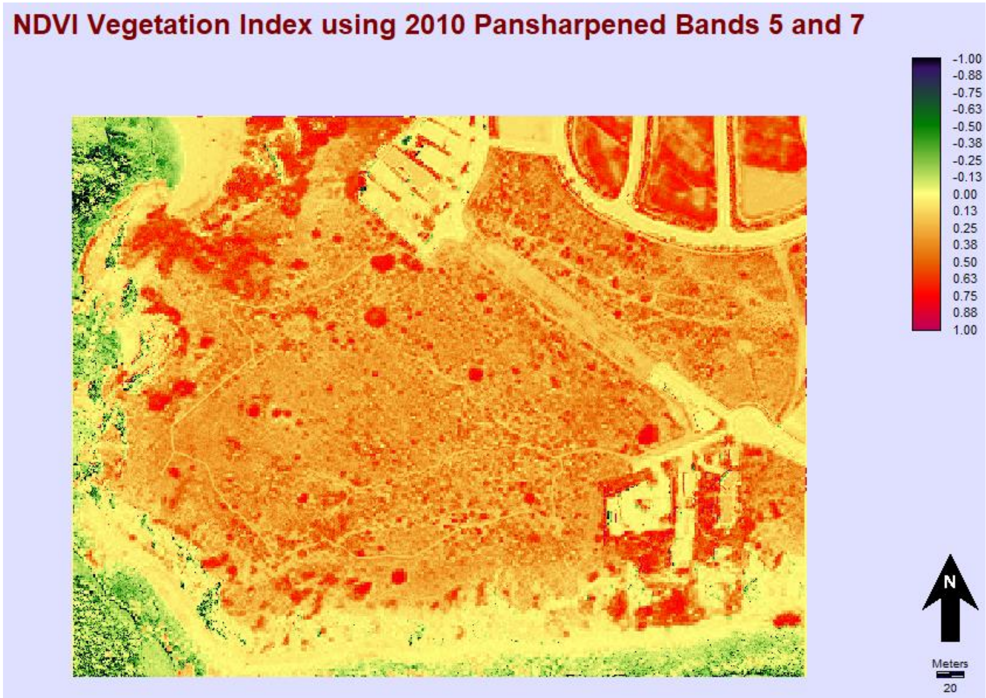

Figure 25. NDVI results for 2010 pansharpened imagery at 0.5 m resolution

Table 12. Percentage of histogram values in distinct ranges

Histogram Values	***Percentage (%) 2010***	***Percentage (%) 2017***
< 0	3	3
0–0.1	8	10
0.2–0.5	78	68
0.6–1.0	11	19

NDVI for 2017 indicated great plant vigor throughout the Preserve, especially in the sunflower habitat, and showed higher values in the image output (Figure 26). This image was also clipped down the 200 m buffer to the Preserve area to calculate habitat values using the histogram. Analysis of the histogram exposed that the mean for NDVI was higher than the 2010 imagery at 0.35, although bare ground cover increased to 10% and shrub values between 0.2–0.5 dropped from 78%–68%. There was an 8% increase in the “dense vegetation” values between

0.6–1.0, which may be explained by rain-induced vigor of categories lemonadeberry and sunflower, as well as younger species in the old road restoration area.

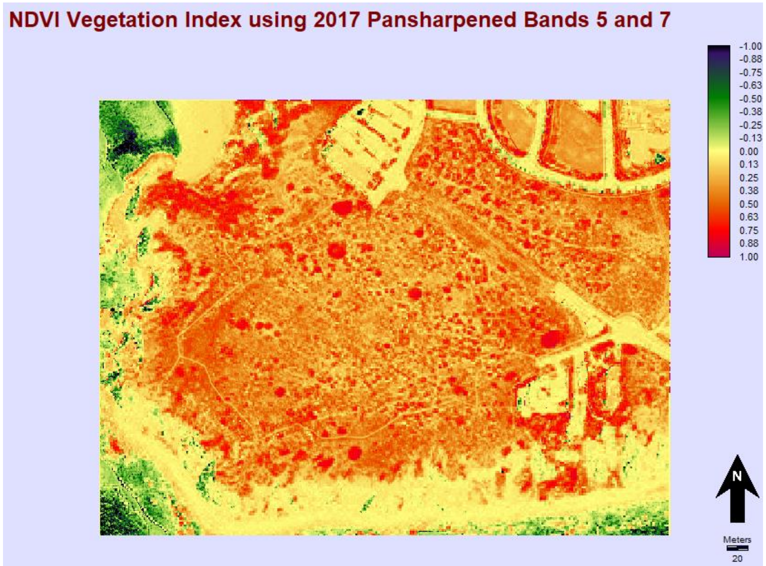

Figure 26. NDVI of 2017 imagery

Using an NDVI overlay tool allows a visual measure of change between years, where red shows where there is more vigor and green exposes decline in healthy vegetation (Figure 27).

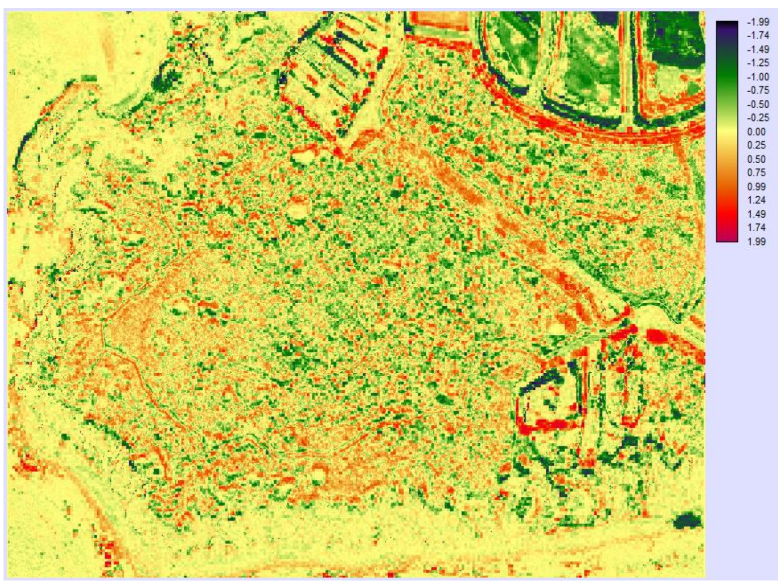

Figure 27. NDVI Overlay showing change in plant vigor between 2010 and 2017

Chapter 5 Discussion and Conclusions

Creating a species distribution model where biologically and statistically significant information is gained for a rare or endangered species is a unique and challenging task especially where the species population and occupied habitat are extremely small. Specific quantitative metrics are used to evaluate model performance and to interpret results, and the maps created from an SDM may not match the anticipated distribution or results (Philips 2017). In this case, finding that the human-associated environmental variables demonstrated the strongest contribution to PPM distribution was unanticipated. There is important information illuminated by the model which can be used for site management as well as future research.

5.1. Model performance

5.1.1. Persistent Importance of Distance to Anthropogenic Features

The anthropogenic feature layer had high permutation importance and percent contribution to every model. In all models, probability of occupancy was 0 near anthropogenic features and increased with distance, reaching a maximum between 100–175 m and declining after 225 m. It is most likely that the low probability near anthropogenic features represents a strong edge effect, while the decline after 225 m is more likely to be an artifact of the site, in that the bluff top ends at that distance and the bluff face down to the ocean is not suitable habitat.

As suggested earlier, it has been found that predator-prey relationships change with the introduction of artificial light (Lima 1998). Developments around the Preserve may be contributing night lighting that have negative consequences to the PPM. Small mammals and rodents change their foraging and movement behavior in response to both natural light and artificial light (Beier 2005, Kotler 1984, Persons and Eason 2016), and this may be restricting PPM from utilizing the full habitat. Predators associated with an urban environment may also be having a deleterious effect on the PPM, as is the case with the near extirpation of the Key Largo woodrat (KLWR) (Winchester et al. 2009). In the case of the KLWR, which is subject to pressures on a true island off the coast of Florida, modeling showed that there were too many pressures on the species to perform a successful species re-introduction on the site (McCleery et al. 2005). This species is part of an ongoing captive breeding recovery program by partnerships the USFWS, similar to the PPM program, and has been well-studied for what environmental variables may contribute to its survivorship (McCleery, Hostetler and Oli 2014). Without management of edge effects, the small mammal species will be limited to population size and restricted to a core area of the Preserve (McCleery, Hostetler, and Oli 2014).

5.1.2. Distance to Trail

The distance to trail variable exhibited the second highest permutation importance, with higher probability of occupancy closest to the trail. Disturbance was a component of the Preserve for years prior to the establishment of the fenced off trail which was intended to protect the core, interior habitat for the PPM and the gnatcatcher. Human impacts kept the vegetation sparse without fencing, as partiers, recreationalists, and motor vehicles maintained a lot of bare ground on site. At present, disturbance is limited to the public trail, except for where the resource managers perform selective vegetation duff removal and thinning. CNLM staff patrol to ensure that dogs and their olfactory influences are not introduced to the Preserve, and the primary activity is foot traffic. There is not much recruitment of annual forb species in this area, but the openness of the trail area may not be as much of a limiting factor as previously thought by managers. In their review of literature of recreational impacts on wildlife, Larson et al. (2016) found that influence on small mammals was minimal. Further research may elucidate why this environmental variable provided such high contribution to the model.

5.1.3. Vegetation types as environmental variables

The best models include sagebrush as the third highest contributor to the model using the measure of permutation importance. The variable response curve suggests that where there is more sagebrush, more mice will be detected. This is also represented well in the graphic output of both the habitat classification and the distribution models. Buckwheat showed quaternary importance and was included in every model. However, the lack of permutation importance from all habitat types leaves further questions about why they do not provide significant contribution to the model. Understanding the role of each vegetation type may also help explain why the northeast corner of the Preserve north of the old road is not being detected as highly suitable habitat.

The vegetation classifications were improved multiple times by increasing training polygons of each habitat type to try to answer further questions about accuracy of classification and species distribution. The results from the classification were satisfactory and the native vegetation change detected was not very different in the images clipped to site compared to the buffered area, and can all be explained by phenomena on the site. It is possible that the woodiness of buckwheat, which was detected by the classification as well as the NDVI, is now providing refuge for competitive species such as the woodrat. It is also possible that the percent cover of healthy sagebrush is associated with PPM because they prefer the area for cover when foraging (Kotler 1984), and a lack of recruitment of new plants is contributing to the limited distribution.

Again, the change in buckwheat is best explained by the increased woodiness of the aging plants which may not have displayed sufficient vigor to have a highly unique spectral signature. (Appendix A). Typically, the shrub grows along the trail and intermixed into the sagebrush within the Preserve; it shades out bare ground with its litter and does not have much robust, new growing vegetation which could serve as food for the PPM. The small increase in bare ground is likely from the area underneath dead shrubs which became more visible with dieback in other shrub species. Sunflower responds to rains with abundant growth and is very distinct in aerial imagery during the peak growing season; the reflectance of vigor and leaf area in lemonadeberry is distinct as well. The near-absent change in sagebrush is to be expected given that there is no new recruitment of young plants and the existing shrubs are aging and experiencing some mortality; in 2017, the plant experienced more vigor than in previous years due to increased rain which supported new growth on the tips. This can be detected in satellite imagery as well as on the ground (Appendix A). The "other" category may represent plant coverage which could not be appropriately classified given the dominant shrub categories; these include coastal cholla (*Cylindropuntia prolifera*), Prickly-pear cactus (*Opuntia littoralis*), rare plants such as *Aphanisma blitoides* and *Euphorbia misera*, as well as deerweed (*Acmispon glaber*) (Appendix A).

5.2. Vegetation layer importance versus NDVI

NDVI was a helpful measure for comparing the results of the classification and further interpreting change in vegetation vigor between years. Bare ground increased 3.4% using the supervised classification method, and 2% by metrics of NDVI comparison. There is no standard description of an NDVI value that reflects leaf litter, nor is there definition of the value for annual forb species. Additional field validation and research may help to understand whether the change in the value of 0.1–0.2 reflects annual forbs which may have decreased between 2010 and 2017.

The lower ranges of shrub cover decreased between 0.2–0.4, while the higher, dense shrub values increased between 0.4–0.8. Comparing this to the classification results may indicate that the large decrease in buckwheat cover is reflected in the lower values, as the woody plants have less leaf reflectance or absorption. Sunflower appears as a dense forest in its blooming period, and sprawling, leaf-covered lemonadeberry may explain the higher shrub values. It is assumed that sagebrush and buckwheat fall into the generalized shrub cover (0.2–0.5) category of NDVI values, and it is interesting to note that there has been no young seedling recruitment of either of these species on the site.

5.2.1. A case for site selection and field knowledge

There is no substitute for field knowledge, and ground truthing is important to all remote sensing and distribution modeling cases. In this study, these were essential validators for testing input variables and understanding model outputs. Furthermore, presence-only modeling methods only require a set of known occurrences together with predictor variables such as topographic, climate, edaphic, biogeographic, and remotely sensed variables (Philips and Dudik 2008). Verification of the trapping points informed the changes and downsampling of the imagery prepare the model to a resolution that was biologically appropriate. Vegetation was confirmed in the field, but a more detailed error matrix could be developed through creation of sample points tested against the computer output. This may further improve the performance of the habitat type environmental variables.

5.3. Effective Preserve Area and Management Recommendations

Determining distinct patches of high quality PPM habitat and calculating the total functional area which support the PPM will be an important part of future research. This thesis took the first step to understanding how edge effects and vegetation contribute to the spatial distribution of the PPM, and may help to inform how future management activities are conducted. Microtopography should be studied with greater detail to see where light is penetrating the Preserve and where it is not so that recommendations can be made to improve the shielding on adjacent streetlights, and to influence the design of the new hotel which is proposed on the northeast side of the Preserve. It has been documented that mice generally show a significant decrease in activity when there is lighting, including moonlight (Persons and Eason 2016). The additional environmental variable to quantify the amount of perimeter lighting influencing the effective preserve area would be created by performing a viewshed analysis from the DEM to see how far light penetrates core areas of the Preserve. The actual Preserve area could be buffered by the light-permeated area to demonstrate the effective functioning habitat.

Domestic animals were not included as environmental variables because of an absence of data, indicating that more data needs to be captured to demonstrate how much predation influences the effective preserve area. Currently, the only data point is one house cat caught on the motion sensing camera in the center of the Preserve, but additional cameras could be set around the perimeter to improve detection. The recreational trail has shown a contribution to the presence of the PPM, and because it wraps around the core area of the Preserve, all mice are found within a specific proximity to this highly-disturbed and trafficked area. However, eliminating the bluff area and other superfluous edges may increase knowledge of how the trail contributes to edge effects and functional habitat.

The models indicate that it is explicitly important to actively manage the vegetation resources on the Preserve, and to consider the level of disturbance and vegetation recruitment that will be needed in areas where PPM are released from the captive breeding program. While there are questions about the contribution of sagebrush and buckwheat, adaptive vegetation management can be performed to test whether removing dead vegetation and allowing new recruitment changes PPM occupancy. Mapping annual forbs and updated manipulations to buckwheat and sagebrush where new growth can provide better cover, forage and habitat will be important for future modeling. Field mapping of annual forb species which are preferred fodder of the PPM, such as *Croton californicus* (Croton), should also be developed as an environmental variable. As Brehme et al. found in their (2014) modeling, the proportion of cover from forbs was the top predictor covariate at all scales, and that Croton was the preferred diet in Dana Point PPM. Forb species may serve as an increasingly important environmental variable to monitor as duff and dead vegetation are removed and more area for native forb species to grow becomes available (Appendix A). There is limited growth of annual species on the Preserve and this may have an important contribution to PPM distribution. Consideration should be given to the idea of collecting and sowing additional native forb seed around the site.

Given that PPM do not occupy areas that are close to houses, an intentional review of the lighting design of the Strands development (as well as the new proposed hotel) should be given. Night lighting was not tested in this model, but it is suggested that it is one anthropogenic influence limiting feature that impacts PPM. Street lamps could better deflect light from the preserve by using shields to direct it back to the housing community.

5.4. Future work

The research model used here and the copious information which has been captured about the PPM lay the framework for numerous possible future studies. This data-analysis model can be run with imagery at larger (5 m) or smaller (20 m) spatial resolution to further determine whether it has more biological meaning. Additional environmental variables can be developed from species information captured during trapping, such as occupancy of competitive species including woodrat.

In conclusion, this research model provides a substantial framework for future research to understand the complex influences on spatial distribution of the PPM on Dana Point Preserve. The influence of bare ground, vegetation, and humans on PPM distribution and proximity is influenced by a range of factors, and this thesis has outlined some possibilities of why this is occurring. An increased understanding of environmental variables may help expand this native population's distribution and abundance as well as to improve habitat conditions. Little habitat remains for this endangered species, and more research is critically important to prevent local extirpation.

References

Aranoff, Stan. 2005. *Remote Sensing for GIS Managers.* Redlands, CA: ESRI Press.

Beier, Paul. 2005. "Effects of Artificial Night Lighting on Terrestrial Mammals." Pages 15–42 *in* Catherine Rich and Travis Longcore, editors. Ecological Consequences of Artificial Night Lighting. Washington, DC: Island Press.

Bhalli, M. N., A. Ghaffar, S. A. Shirazi and N. Parveen. 2013. "An analysis of the normalized difference vegetation index (NDVI) and its relationship with the population distribution of Faisalabad, Pakistan." *Pakistan Journal of Science* 65(4): 496–502.

Boyd, D.S. and F.M. Danson. 2005. "Satellite Remote Sensing of Forest Resources: three decades of research development." *Progress in Physical Geography* 29(1): 1–26.

Brehme, C.S., J. Sebes, T. Matsuda, D. Clark, and R.N. Fisher. 2014. "MCBCP Pacific Pocket Mouse Monitoring Results for 2013 and Multi-Year Trend Analysis from 2012 to 2013. Prepared for AC/S Environmental Security, Marine Corps Base, Camp Pendleton." *U.S. Geological Survey (USGS) Publication*. 1-69.

Carmel, Yohay, and Ronen Kadmon. 1998. "Computerized Classification of Mediterranean Vegetation Using Panchromatic Aerial Photographs." *Journal of Vegetation Science* 9 (3): 445–454.

Center for Natural Lands Management (CNLM). 2008. 2007-2008 Annual Report for the Dana Point Headlands Preserve. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Center for Natural Lands Management (CNLM). 2010. Shapefile for Pacific Pocket Mouse presence locations in 2009. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Center for Natural Lands Management (CNLM). 2014. CNLM 2013 Pacific Pocket Mouse Habitat Enhancement Project on the Dana Point Preserve. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Center for Natural Lands Management (CNLM). 2016. Dana Point Headlands Preserve 2016 Pacific Pocket Mouse Survey Results. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Center for Natural Lands Management (CNLM). 2018. PPM Summary Table Draft January 12, 2018. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Ceradini, Joseph P. and Anna D. Chalfoun. 2017. "Species' traits help predict small mammal responses to habitat homogenization by an invasive grass." *Ecological Applications* 27: 1451–1465.

Cianfrani, C., G. Le Lay, A. Hirzel, and A. Loy. 2010. "Do habitat suitability models reliably predict the recovery areas of threatened species?” *The Journal of Applied Ecology* 47(2): 421–430.

Coates, A., P. Dennison, D. Roberts, D, and K. Roth. 2015. “Monitoring the Impacts of Severe Drought on Southern California Chaparral Species using Hyperspectral and Thermal Infrared Imagery.” *Remote Sensing* 7(11): 14276–14291.

Dark, Shawna J., and Danielle Bram. 2007. "The modifiable areal unit problem (MAUP) in physical geography." *Progress in Physical Geography*. 31(5): 471–479.

Dennison, Philip E. and Dar A. Roberts. 2003a. “The effects of vegetation phenology on endmember selection and species mapping in southern California chaparral.” *Remote Sensing of Environment* 87: 295–309.

Digital Globe. 2009. White paper on the benefits of the 8 spectral bands of WorldView-2. www.digitalglobe.com.

Dennison, Philip E. and Dar A. Roberts. 2003b. “Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE.” *Remote Sensing of Environment* 87: 123–135.

Dodd, Shauna, Phil Brylski, D. Laabs, Steve Montgomery, and W. Spencer. 1998. Final report 1997 Pacific Pocket Mouse (*Perognathus longimembris pacificus*) surveys on the Dana Point Headlands, Orange County, California. Unpublished report prepared for the U. S. Fish and Wildlife Service, California Department of Fish and Game, and The Nature Reserve of Orange County. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Dodd, Shauna, William Miller. Phil Brylski and Steven Montgomery. 2009. Addendum to the Pilot Monitoring Project for the Pacific Pocket Mouse; CNLM Dana Point Preserve, Orange County, California Report on Pacific Pocket Mouse. https://cnlm.app.box.com/files/0/f/125752701/PPM.

Ecke, Frauke. “Effects of landscape patterns on small mammal abundance.” Doctoral thesis. Luleå University of Technology, 2003. http://ltu.diva-portal.org/smash/get/diva2:989802/FULLTEXT01.pdf.

Elith, Jane and John Leathwick, R. 2009. "Species Distribution Models: Ecological Explanation and Prediction across Space and Time." Annual Review of Ecology 40: 677–697.

Elith, Jane, S. J. Phillips, T. Hastie, M. Dudík, Y. E. Chee, & C. J. Yates. 2011. “A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions.* 17(1): 43–57.

Engler, Robin, Antoine Guisan, and Luca Rechsteiner. 2004. “An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo-absence data”. *Journal of Applied Ecology* 41 (3): 263–274.

Earth Observation through Remote Sensing (EROS). 2013. “How to Interpret Common False

Color Images.” https://earthobservatory.nasa.gov/Features/FalseColor/page6.php.

--- . 2017. “How to pan-sharpen Landsat imagery.” https://earthobservatory.nasa.gov/blogs/earthmatters/2017/6/13/how-to-an-sharpen-imagery.

Federal Register. 1994. Endangered and Threatened Wildlife and Plants; Determination of Endangered Status for the Pacific Pocket Mouse. 5O CFR Part 17. RIN 1018—AC39.

Fernández, Néstor, José M. Paruelo, and Miguel Delibes. 2010. “Ecosystem functioning of protected and altered Mediterranean environments: A remote sensing classification in Doñana, Spain.” *Remote Sensing of Environment* 114: 211–220.

Fielding, A.H. and J.F. Bell. 1997. “For review of predication errors in conservation presence/absence models. *Environmental Conservation* 24(1): 38–49.

Gastón, Aitor, Carlos Ciudad, María C. Mateo-Sánchez, Juan I. García-Viñas, César López-Leiva, Alfredo Fernández-Landa, Miguel Marchamalo, Jorge Cuevas, Begoña de La Fuente, Marie-Josée Fortin, Santiago Saura. 2017. “Species’ Habitat Use Inferred from Environmental Variables at Multiple Scales: How Much We Gain from High-resolution Vegetation Data?” *International Journal of Applied Earth Observations and Geoinformation* 55: 1–8.

Guevara, Lazaro, Beth E. Gerstner, Jamie M. Kass, and Robert P. Anderson. 2018. “Toward ecologically realistic predictions of species distributions: A cross-time example from tropical montane cloud forests.” *Global Change Biology* 24: 1511–1522.

Guisan, Antoine and Niklaus E. Zimmerman. 2000. "Predictive Habitat Distribution Models in Ecology." *Ecological Modeling* 135: 147–186.

Hernandez, P. A., C. H. Graham, L. L. Master and Albert D. L. 2006. “The effect of sample size and species characteristics on performance of different species distribution modeling methods.” *Ecography* 29: 773–785.

Kamiran, N., and M. L. R. Sarker. 2014. "Exploring the Potential of High Resolution Remote Sensing Data for Mapping Vegetation and the Age Groups of Oil Palm Plantation." *IOP Conference Series: Earth and Environmental Science* 18(1): 6.

Kim, Seong-Hee, John Tschirhart, and Steven W. Buskirk. 2007. “Reconstructing past population processes with general equilibrium models: House mice in Kern County, California, 1926–1927.” *Ecological Modelling*. 209: 235–248.

Kotler, Burt. 1984. “Risk of Predation and the Structure of Desert Rodent Communities *Ecology* 65(3): 689–701.

Irl, Severin D.H. and Carl Beierkuhnlein. 2011. "Distribution of Endemic Plant Species on an

Oceanic Island – a Geospatial Analysis of La Palma (Canary Islands)." *Procedia Environmental Sciences* 7: 170–75.

Lande, R. 1995. "Mutation and conservation." *Conservation Biology* 9: 782–791.

Larson, C. L., S. E. Reed, A. M. Merenlender, and K. R. Crooks. 2016. "Effects of Recreation on Animals Revealed as Widespread through a Global Systematic Review
Effects of Recreation on Animals Revealed as Widespread through a Global Systematic Review." *PLOS One* 11(12): 1–21.

Levin, Simon A. 1992. "The problem of pattern and scale in ecology." *Ecology* 73(6): 1943–1967.

Lima, Steven L. 1998. "Stress and Decision Making under the Risk of Predation: Recent Developments from Behavioral, Reproductive, and Ecological Perspectives." *Advances in the Study of Behavior* 27: 215–290.

Longcore, Travis, Christine Lam, S. Kobernus, Patrick Polk, and Eben Wilson. 2010. "Extracting Useful Data from Imperfect Monitoring Schemes: Endangered Butterflies at San Bruno Mountain, San Mateo County, California (1982–2000) and Implications for Habitat Management." *Journal of Insect Conservation* (14)4: 335–346.

Longcore, Travis H. and Kendall H. Osborne. 2015. "Butterflies Are Not Grizzly Bears: Lepidoptera Conservation in Practice." Pages 161–192 *in* Butterfly Conservation in North America: Efforts to Help Save Our Charismatic Microfauna. Springer Netherlands.

McCleery, Robert A., Roel R. Lopez, Nova J. Silvy, and William E. Grant. 2005."Effectiveness of supplemental stockings for the endangered Key Largo woodrat." *Biological Conservation* 124(1): 27–33.

McCleery, Robert Jeffrey A. Hostetler, and Madan K. Oli. 2014. Better off in the wild? Evaluating a captive breeding and release program for the recovery of an endangered rodent. *Biological Conservation*. 169: 198–205.

Merow, Cory, Matthew J. Smith and John A. Silander, Jr. 2013. "A practical guide to Maxent for modeling species' distributions: what it does, and why inputs and settings matter." *Ecography* 36: 1058–1069.

Merrill, Korie. Personal communication February 25, 2018. Notes on PPM working group meeting conversations.

Miller, William. 2018. Pacific Pocket Mouse Trapping and Monitoring Surveys at the Dana Point Headlands 1993–2017.

Millard, K., A. Redden, M. Webster, and T. Stewart. 2013. "Use of GIS and High Resolution

LiDAR in Salt Marsh Restoration Site Suitability Assessments in the Upper Bay of Fundy, Canada." *Wetlands Ecology and Management* 21(4): 243–262.

Mu, Jing, Nanjang Luo, Weil Chang, Kaiyi Huang and Mingchang Shi. 2013. “Predicting and mapping the spatial distribution of *Chamaecyparis formosensis* in central Taiwan in a GIS with species distribution models.” *Arcta Ecologica Sinica* 33: 325–331.

Mustafa, Y.T., H.N. Habeeb, A. Stein, F.Y. Sulaiman. 2015. “Identification and mapping tree species in urban areas using WorldView2 imagery.” *International Society of Photogrammetry and Remote Sensing (ISPRS) Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Volume II-2/W2.

O'Leary, J. F. 1990. “California coastal sage scrub: general characteristics and considerations for biological conservation.” Pages 24–41 *in* A. A. Schoenherr, editor. Endangered plant communities of southern California. Southern California Botanists, Claremont, California.

Persons, William E. and Perri Eason. 2017. “Human activity and habitat type affect perceived predation risk in urban white-footed mice.” *Ethology* 123:348–356.

Phillips, Steven J., Miroslav Dudík, and Robert E. Schapire. Maxent software for modeling species niches and distributions (Version 3.4.1). Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 1-6-2018.

Phillips, Steven J., Robert P. Anderson, and Robert E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190: 231–259.

Phillips, Steven J., and Miroslav Dudik. 2008. "Modeling of Species Distributions with Maxent: New Extensions and a Comprehensive Evaluation." *Ecography* 31: 161–75.

Phillips, Steven J., Robert P. Anderson, Miroslav Dudík, Robert E. Schapire and Mary E. Blair. 2017. “Opening the black box: an open-source release of Maxent.” *Ecography* 40: 887–893.

Radosavljevic, A., & Anderson, R. P. 2014. “Making better Maxent models of species distributions: complexity, overfitting and evaluation.” *Journal of Biogeography* 41(4): 629–643.

Roberts, Dar A., Philip E. Dennison, Keely L. Roth, Kenneth Dudley, and Glynn Hulley. 2015. “Relationships between dominant plant species, fractional cover and Land Surface Temperature in a Mediterranean ecosystem.” *Remote Sensing of Environment* 167:152–167.

Santosa, Xavier et al. 2006. “Inferring habitat-suitability areas with ecological modelling techniques and GIS: A contribution to assess the conservation status of *Vipera latastei*.” *Biological Conservation* 130: 416–425.

Shirazi, Safdar Ali. 2012. "Spatial analysis of NDVI and density of population: A case study of Lahore, Pakistan. *Science International* 24 (3): 11–23.

Schaffer-Smith, Danica, Jennifer J. Swenson, and Antonio J. Boveda-Penalba. 2016. “Rapid conservation assessment for endangered species using habitat connectivity models.” *Environmental Conservation* 43 (3): 221–230.

Smolek, Andrea. 2015. “Spatial distribution of the greater sage-grouse in the powder river basin in northeastern Wyoming.” Master’s thesis, University of Southern California. http://spatial.usc.edu/wp-content/uploads/2015/10/SmolekAudra.pdf.

Thibault, Katherine M, S.K. Morgan Ernest, Ethan P. White, James H. Brown and Jacob R. Goheen. 2010. “Long-term insights into the influence of precipitation on community dynamics in desert rodents.” *Journal of Mammalogy* 91(4): 787–797.

Timm, Susan. 2008. Using Remote Sensing, GIS, and Landscape Ecology Techniques in Wildland Management: The Influence of Spatial Errors in Species Occurrence Data Used in Distribution Models. Master’s thesis for California State University at Long Beach. https://search-proquest-com.libproxy1.usc.edu/docview/304844292.

United States Fish and Wildlife Service (USFWS). 1998. “Recovery Plan for the Pacific Pocket Mouse.” https://www.fws.gov/carlsbad/SpeciesStatusList/RP/19980928_RP_PPM.pdf.

United States Geological Survey. 2015. “NDVI, the Foundation for Remote Sensing”. https://phenology.cr.usgs.gov/ndvi_foundation.php.

United States Geological Survey. 2017. “2012–2016 California Drought: Historical Perspective”. https://ca.water.usgs.gov/california-drought/california-drought-comparisons.html.

Wang, Qifan, Zhenhong Jia, Xizhong Qin, Jie Yang, Yingjie Hu. 2011. “A New Technique for Multispectral and Panchromatic Image Fusion.” *Procedia Engineering* 24: 182–186.

Warner, Timothy and David J. Campagna. 2013. *Remote Sensing with IDRISI: A Beginner’s Guide*. Hong Kong: Geocarto International Centre Ltd.

Warren, D., and S. Seifert. 2011. “Ecological niche modeling in Maxent: The importance of model complexity and the performance of model selection criteria.” *Ecological Applications* 21(2): 335–342.

Weather Underground. Precipitation records for Santa Ana, California. Accessed March 8, 2018. https://www.wunderground.com/history/airport/KSNA/

Winchester, Christopher, Steven B. Castleberry & Michael T. Mengak. 2009. “Evaluation of factors restricting distribution of the endangered Key Largo woodrat.” *Journal of Wildlife Management* 73(3): 374–379.

Appendix A

Images of the Preserve's vegetation were taken on April 16, 2018 by Sarah Godfrey.

1) Aging buckwheat on the Preserve exhibits woodiness and lack of vigor

2) Vigorous bush sunflower during peak growing months (April 2018)

3) Native forb species which thrive after duff removal and serve as food for the PPM include *Pseudognaphalium californicum* and *Croton californica* (April 2018)

4) Non-dominant species that may have been detected as “other” or caused spectral mixing in classification include cholla, prickly-pear, and deerweed (April 2018)

5) California Sagebrush with plant mortality and vigorous new growth in peak growing months (April 2018)